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# 2017 Financial Risk Manager (FRM®)

## Exam Part II

## Credit Risk Measurement and Management

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Sixth Custom Edition for the
Global Association of Risk Professionals

GARP | Global Association of Risk Professionals

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# Contents

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## Chapter 2 The Credit Analyst 31



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## Chapter 11 Collateral 245



## Chapter 12 Central Counterparties 261



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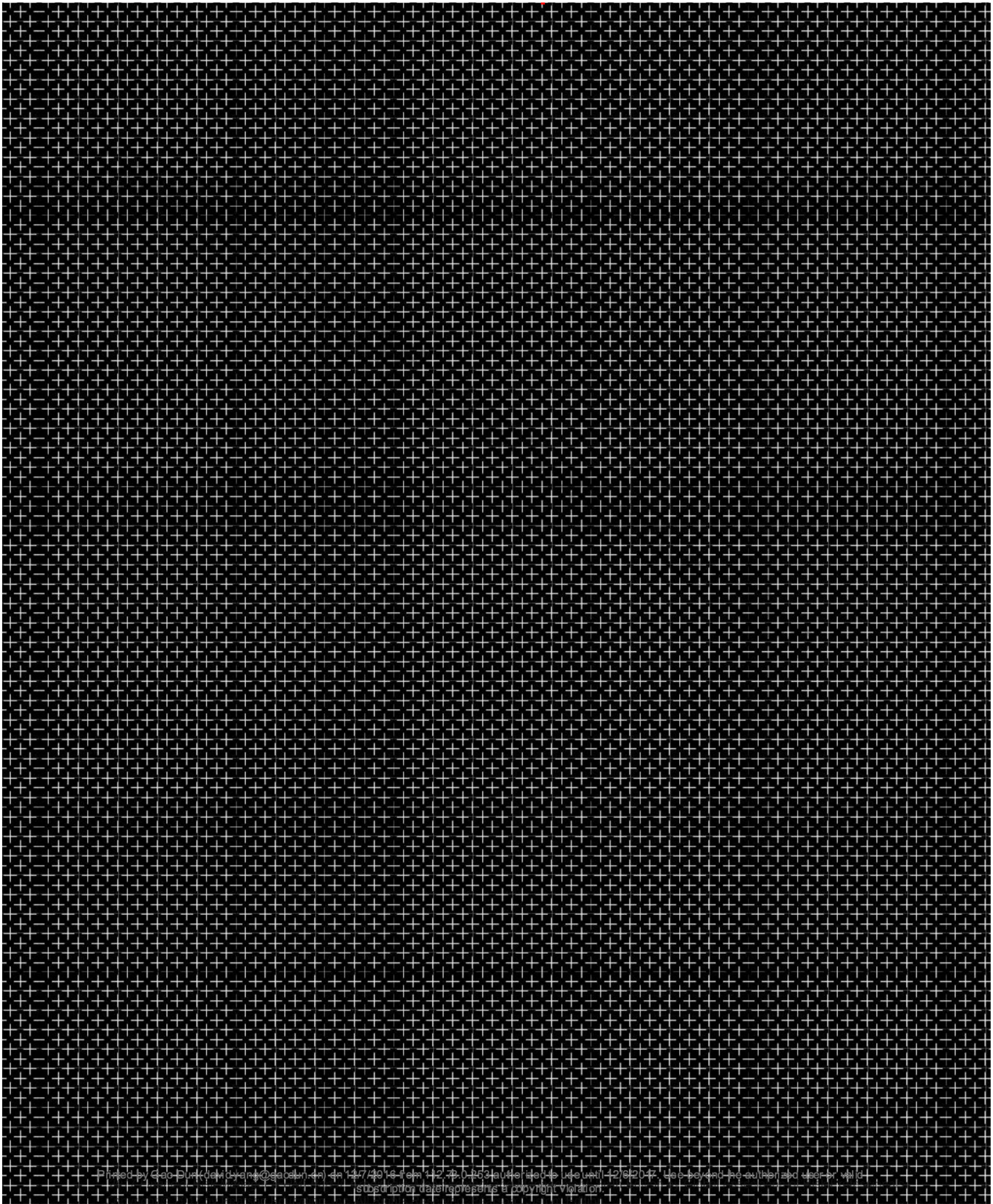

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# 1 The Credit Decision

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## Learning Objectives

After completing this reading you should be able to:

- Define credit risk and explain how it arises using examples.
- Explain the components of credit risk evaluation.
- Describe, compare, and contrast various credit risk mitigants and their role in credit analysis.
- Compare and contrast quantitative and qualitative techniques of credit risk evaluation.
- Compare the credit analysis of consumers, corporations, financial institutions, and sovereigns.
- Describe quantitative measurements and factors of credit risk, including probability of default, loss given default, exposure at default, expected loss, and time horizon.
- Compare bank failure and bank insolvency.

*Excerpt is Chapter 1 of* The Bank Credit Analysis Handbook, *Second Edition, by Jonathan Golin and Philippe Delhaise.*



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CREDIT. Trust given or received; expectation of future payment for property transferred, or of fulfillment or promises given; mercantile reputation entitling one to be trusted;—applied to individuals, corporations, communities, or nations; as, to buy goods on credit.

—Webster's Unabridged Dictionary, 1913 Edition

A bank lives on credit. Till it is trusted it is nothing; and when it ceases to be trusted, it returns to nothing.

—Walter Bagehot[1]

People should be more concerned with the return of their principal than the return on their principal.

—Jim Rogers[2]

The word *credit* derives from the ancient Latin *credere*, which means "to entrust" or "to believe."[3] Through the intervening centuries, the meaning of the term remains close to the original; lenders, or *creditors*, extend funds—or "credit"—based upon the belief that the borrower can be *entrusted* to repay the sum advanced, together with interest, according to the terms agreed. This conviction necessarily rests upon two fundamental principles; namely, the creditor's confidence that:

1. The borrower is, and will be, *willing to repay* the funds advanced
2. The borrower has, and will have, the *capacity to repay* those funds

The first premise generally relies upon the creditor's knowledge of the borrower (or the borrower's reputation), while the second is typically based upon the creditor's understanding of the borrower's financial condition, or a similar analysis performed by a trusted party.[4]

## DEFINITION OF CREDIT

Consequently, a broad, if not all-encompassing, definition of credit is the realistic belief or expectation, upon which a lender is willing to act, that funds advanced will be repaid in full in accordance with the agreement made between the party lending the funds and the party borrowing the funds.[5] Correspondingly, *credit risk* is the possibility that events, as they unfold, will contravene this belief.

### Creditworthy or Not

Put another way, a sensible individual with money to spare (i.e., savings or capital) will not provide credit on a commercial basis[6]—that is, will not make a loan—unless she

[1] Walter Bagehot, *Lombard Street: A Description of the Money Market* (1873), hereafter Lombard Street. Bagehot (pronounced "badget" to rhyme with "gadget") was a nineteenth-century British journalist, trained in the law, who wrote extensively about economic and financial matters. An early editor of *The Economist*, Bagehot's *Lombard Street* was a landmark financial treatise published four years before his death in 1877.

[2] Various attributions; see for example Global-Investor.com; *500 of the Most Witty, Acerbic and Erudite Things Ever Said About Money* (Harriman House, 2002). Author of *Adventure Capitalist* and *Investment Biker*, Jim Rogers is best known as one of the world's foremost investors. As co-founder of the Quantum fund with George Soros in 1970, Rogers's extraordinary success as an investor enabled him to retire at the age of 37. He remains in the public eye, however, through his books and commentary in the financial media.

[3] See, for example, "credit. . . . Etymology: Middle French, from Old Italian *credito*, from Latin *creditum*, something entrusted to another, loan, from neuter of *creditus*, past participle of *credere*, to believe, entrust." *Merriam-Webster Online Dictionary*, www.m-w.com. *Webster's Revised Unabridged Dictionary* (1913) defines the term to mean: "trust given or received; expectation of future payment for property transferred, or of fulfillment or promises given; mercantile reputation entitling one to be trusted; applied to individuals, corporations, communities, or nations; as, to buy goods on credit." www.dictionary.net/credit. Walter Bagehot, whose quoted remarks led this chapter, gave the meaning of the term as follows: "Credit means that a certain confidence is given, and a certain trust reposed. Is that trust justified? And is that confidence wise? These are the cardinal questions. To put it more simply, credit is a set of promises to pay; will those promises be kept?" (Bagehot, *Lombard Street*).

[4] This is assuming, of course, that the financial condition of the borrower has been honestly and openly represented to the creditor through the borrower's financial statements. The relevance of the assumption remains important, as the discussions concerning financial quality later in the book illustrate.

[5] As put by John Locke, the seventeenth-century British philosopher, "credit [is] nothing but the expectation of money within some limited time . . . money must be had, or credit will fail."—vol. 4 of *The Works of John Locke in Nine Volumes*, 12th ed. (London: Rivington, 1824), www.econlib.org. Credit exposure (exposure to credit risk) can also arise indirectly as a result of a transaction that does not have the character of loan, such as in the settlement of a securities transaction. The resultant settlement risk is a subset of credit risk. Aside from settlement risk, however, credit risk implies the existence of a financial obligation, either present or prospective.

[6] The phrase "on a commercial basis" is used here to mean in an "arm's-length" business dealing with the object of making a commercial profit, in contrast to a transaction entered into because of friendship, family ties, or dedication to a cause, or as a result of any other noncommercial motivation.



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> **SOME OTHER DEFINITIONS OF CREDIT**
>
> *Credit [is] nothing but the expectation of money, within some limited time.*
>
> —John Locke
>
> *Credit is at the heart of not just banking but business itself. Every kind of transaction except, maybe, cash on delivery—from billion-dollar issues of securities to getting paid next week for work done today—involves a credit judgment. . . . Credit . . . is like love or power; it cannot ultimately be measured because it is a matter of risk, trust, and an assessment of how flawed human beings and their institutions will perform.*
>
> —R. Taggart Murphy[7]

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believes that the borrower has both the requisite willingness and capacity to repay the funds advanced. As suggested, for a creditor to form such a belief rationally, she must be satisfied that the following two questions can be answered in the affirmative:

1. Will the prospective borrower be *willing*, so long as the obligation exists, to repay it?
2. Will the prospective borrower be *able* to repay the obligation when required under its terms?

Traditional credit analysis recognizes that these questions will rarely be amenable to definitive yes/no answers. Instead, they call for a judgment of probability. Therefore, in practice, the credit analyst has traditionally sought to answer the question:

What is the likelihood that a borrower will perform its financial obligations in accordance with their terms?

All other things being equal, the closer the probability is to 100 percent, the less likely it is that the creditor will sustain a loss and, accordingly, the lower the credit risk. In the same manner, to the extent that the probability is below 100 percent, the greater the risk of loss, and the higher the credit risk.

## Credit Risk

Credit risk and the concomitant need for the estimation of that risk surface in many business contexts. It emerges, for example, when one party performs services for another and then sends a bill for the services rendered for payment. It also arises in connection with the settlement of transactions—where one party has advanced payment to the other and awaits receipt of the items purchased or where one party has advanced the items purchased and awaits payment. Indeed, most enterprises that buy and sell products or services, that is practically all businesses, incur varying degrees of credit risk. Only in respect to the simultaneous exchange of goods for cash can it be said that credit risk is essentially absent.

While nonfinancial enterprises, particularly small merchants, can eliminate credit risk by engaging only in *cash and carry* transactions, it is common for vendors to offer credit to buyers to facilitate a particular sale, or merely because the same terms are offered by their competitors. Suppliers, for example, may offer *trade credit* to purchasers, allowing some reasonable period of time, say 30 days, to settle an invoice. Risks arising from trade credit form a transition zone between settlement risk and the creation of a more fundamental financial obligation.

It is evident that as opposed to trade credit, as well as settlement risk that emerges during the consummation of a sale or transfer, fundamental financial obligation arises where sellers offer explicit financing terms to prospective buyers. This type of credit extension is particularly common in connection with purchases of big ticket items by consumers or businesses. As an illustration, automobile manufacturers frequently offer customers attractive finance terms as an incentive. Similarly, a manufacturer of electrical generating equipment may offer financing terms to facilitate the sale of the machinery to a power utility company. Such credit risk is essentially indistinguishable from that created by a bank loan.

In contrast to nonfinancial firms, which can choose to operate on a cash-only basis, banks by definition cannot avoid credit risk. The acceptance of credit risk is inherent to their operation since the very raison d'être of banks is the supply of credit through the advance of cash and the corresponding creation of financial obligations. Success in banking is attained not by avoiding risk but by effectively selecting and managing risk. In order to better manage risk, it follows

[7] R. Taggart Murphy, *The Real Price of Japanese Money* (London: Weidenfeld & Nicolson, 1996), 49. Murphy's book was published in the United States as *The Weight of the Yen: How Denial Imperils America's Future and Ruins an Alliance* (New York: W. W. Norton, 1996). Although Taggart's book is primarily concerned with the U.S.–Japan trade relationship as it evolved during the post–World War II period, Chapter 2 of the text, entitled "The Credit Decision," provides an instructive sketch of the function of credit assessment in the commercial banking industry.



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CASE STUDY: PREMODERN CREDIT ANALYSIS

***The date: The last years of the nineteenth century***

***The place: A small provincial bank in rural England—let us call the institution Wessex Bank—located in the market town of Westport***

Simon Brown, a manager of Wessex Bank, is contemplating a loan to John Smith, a newly arrived merchant who has recently established a bicycle shop in the town's main square. Smith's business has only been established a year or so, but trade has been brisk, judging by the increasing number of two-wheelers that can be seen on Westport's streets and in the surrounding countryside.

Yesterday, Smith called on Brown at his office, and made an application for a loan. The merchant's accounts, Brown noted, showed a burgeoning business, but one in need of capital to fund inventory expansion, especially in preparation for spring and summer, when prospective customers flock to the shop. While some of Smith's suppliers provide trade credit, sharply increasing demand for cycles and limited supply have caused them to tighten their own credit terms. Smith projected, not entirely unreasonably, thought Brown, that he could increase his turnover by 30 percent if he could acquire more stock and promise customers quick delivery.

When asked by Brown, Smith said he would be willing to pledge his assets, including the shop's inventory, as collateral to secure the loan. But Brown, as befits his reputation as a prudent banker, remained skeptical. Those newfangled machines were, in his view, dangerous vehicles and very likely a passing fad.

During the interview, Smith mentioned in passing that he was related on his father's side to Squire Roberts, a prosperous local landowner well known to Brown and a longstanding customer of Wessex Bank. Just that morning, Brown had seen the old gentleman at the post office, and, to his surprise, Roberts struck up a conversation about the weather and the state of the timber trade, and mentioned that he had heard his nephew had called on Brown recently. Before Brown had time to register the news that Roberts was Smith's uncle, Roberts volunteered that he was willing to vouch for Smith's character—"a fine lad"—and, moreover, added that he was willing to guarantee the loan.

Brown decided to have another look at Smith's loan application. Rubbing his chin, he reasoned to himself that the morning's news presented another situation entirely. Not only was Smith not the stranger he was before, but he was also a potentially good customer. With confirmation of his character from Roberts, Brown was on his way to persuading himself that the bank was probably adequately protected. Roberts's indication that he would guarantee the loan removed any remaining doubts. Should Smith default, the bank could hold the well-off Roberts liable for the obligation. Through the prospective substitution of Robert's creditworthiness for that of Smith's the bank's credit risk was considerably reduced. The last twinge of anxiety having been removed, Brown decided to approve the loan to Smith.

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that banks must be able to estimate the credit risk to which they are exposed as accurately as possible. This explains why banks almost invariably have a much greater need for credit analysis than do nonfinancial enterprises, for which, again by definition, the shouldering of credit risk exposure is peripheral to their main business activity.

## Credit Analysis

For purposes of practical analysis, credit risk may be defined as the risk of monetary loss arising from any of the following four circumstances:

1. The default of a counterparty on a fundamental financial obligation
2. An increased probability of default on a fundamental financial obligation
3. A higher than expected loss severity arising from either a lower than expected recovery or a higher than expected exposure at the time of default
4. The default of a counterparty with respect to the payment of funds for goods or services that have already been advanced (settlement risk)

The variables most directly affecting relative credit risk include the following four:

1. The capacity and willingness of the obligor (borrower, counterparty, issuer, etc.) to meet its obligations
2. The external environment (operating conditions, country risk, business climate, etc.) insofar as it affects the probability of default, loss severity, or exposure at default
3. The characteristics of the relevant credit instrument (product, facility, issue, debt security, loan, etc.)



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4. The quality and sufficiency of any credit risk mitigants (collateral, guarantees, credit enhancements, etc.) utilized

Credit risk is also influenced by the length of time over which exposure exists. At the portfolio level, correlations among particular assets together with the level of concentration of particular assets are the key concerns.

## Components of Credit Risk

At the level of practical analysis, the process of credit risk evaluation can be viewed as formulating answers to a series of questions with respect to each of these four variables. The following questions are intended to be suggestive of the line of inquiry that might be pursued.

**The Obligor's Capacity and Willingness to Repay**

- What is the capacity of the obligor to service its financial obligations?
- How likely will it be to fulfill that obligation through maturity?
- What is the type of obligor and usual credit risk characteristics associated with its business niche?
- What is the impact of the obligor's corporate structure, critical ownership, or other relationships and policy obligations upon its credit profile?

**The External Conditions**

- How do country risk (sovereign risk) and operation conditions, including systemic risk, impinge upon the credit risk to which the obligee is exposed?
- What cyclical or secular changes are likely to affect the level of that risk? The obligation (product): What are its credit characteristics?

**The Attributes of Obligation from Which Credit Risk Arises**

- What are the inherent risk characteristics of that obligation? Aside from general legal risk in the relevant jurisdiction, is the obligation subject to any legal risk specific to the product?
- What is the tenor (maturity) of the product?
- Is the obligation secured; that is, are credit risk mitigants embedded in the product?
- What priority (e.g., senior, subordinated, unsecured) is assigned to the creditor (obligee)?
- How do specific covenants and terms benefit each party thereby increasing or decreasing the credit risk to which the obligee is exposed? For example, are there any call provisions allowing the obligor to repay the obligation early; does the obligee have any right to convert the obligation to another form of security?
- What is the currency in which the obligation is denominated?
- Is there any associated contingent/derivative risk to which either party is subject?

**The Credit Risk Mitigants**

- Are any credit risk mitigants—such as collateral—utilized in the existing obligation or contemplated transaction? If so, how do they impact credit risk?
- If there is a secondary obligor, what is its credit risk?
- Has an evaluation of the strength of the credit risk mitigation been undertaken?

In this book, our primary focus will be on the obligor bank and the environment in which it operates, with consideration of the credit characteristics of specific financial products and accompanying credit risk mitigants relegated to a secondary position. The reasons are twofold. One, evaluation of the first two elements form the core of bank credit analysis. This is invariably undertaken before adjustments are made to take account of the impact of the credit characteristics of particular financial products or methods used to modify those characteristics. Two, to do justice to the myriad of different types of financial products, not to speak of credit risk mitigation techniques, requires a book in itself and the volume of material to be covered with regard to the obligor and the operating environment is greater than a single volume.

## Credit Risk Mitigation

While the foregoing query concerning the likelihood that a borrower will perform its financial obligations is simple, its simplicity belies the intrinsic difficulties in arriving at a satisfactory, accurate, and reliable answer. The issue is not just the underlying probability of default, but the degree of uncertainty associated with forecasting this probability. Such uncertainty has long led lenders to seek security in the form of collateral or guarantees, both to mitigate credit risk and, in practice, to circumvent the need to analyze it altogether.



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## Collateral—Assets That Function to Secure a Loan

*Collateral* refers to assets that are either deposited with a lender, conditionally assigned to the lender pending full repayment of the funds borrowed, or more generally to assets with respect to which the lender has the right to obtain title and possession in full or partial satisfaction of the corresponding financial obligation. Thus, the lender who receives collateral and complies with the applicable legal requirements becomes a *secured creditor*, possessing specified legal rights to designated assets in case the borrower is unable to repay its obligation with cash or with other current assets.[8] If the borrower defaults, the lender may be able to seize the collateral through foreclosure[9] and sell it to satisfy outstanding obligations. Both secured and unsecured creditors may force the delinquent borrower into bankruptcy. The secured creditor, however, benefits from the right to sell the collateral without necessarily initiating bankruptcy proceedings, and stands in a better position than unsecured creditors once such proceedings have commenced.[10]

It is evident that, since collateral may generally be sold on the default of the borrower (the *obligor*), it provides security to the lender (the *obligee*). The prospective loss of collateral also gives the obligor an incentive to repay its obligation. In this way, the use of collateral tends to lower the probability of default, and, more significantly, reduce the severity of the creditor's loss in the event of default, by providing the creditor with full or partial recompense for the loss that would otherwise be incurred. Overall, collateral tends to reduce, or mitigate, the credit risk to which the lender is exposed, and it is therefore classified as a *credit risk mitigant.*

Since the amount advanced is known, and because collateral can normally be appraised with some degree of accuracy—often through reference to the market value of comparable goods or assets—the credit decision is considerably simplified. By obviating the need to consider the issues of the borrower's willingness and capacity, the question—*What is the likelihood that a borrower will perform its financial obligations in accordance with their terms?*—can be replaced with one more easily answered, namely: "Will the collateral provided by the prospective borrower be sufficient to secure repayment?"[11]

As Roger Hale, the author of an excellent introduction to credit analysis, succinctly puts it: "If a pawnbroker lends money against a gold watch, he does not need credit analysis. He needs instead to know the value of the watch."[12]

## Guarantees

A *guarantee* is the promise by a third party to accept liability for the debts of another in the event that the primary obligor defaults, and is another kind of credit risk mitigant. Unlike collateral, the use of a guarantee does not eliminate the need for credit analysis, but simplifies it by making the guarantor instead of the borrower the object of scrutiny.

Typically, the guarantor will be an entity that either possesses greater creditworthiness than the primary obligor,

[8] There are four basic types of collateral: (1) real or personal property (including inventory, trade goods, and intangible property); (2) negotiable instruments (including securities); (3) other financial collateral (i.e., other financial assets); and (4) floating charges on business assets. *Current assets* refers to assets readily convertible to cash. These are also known as *liquid assets.*

[9] *Foreclosure* is a legal procedure to enforce a creditor's rights with respect to collateral pledged by a delinquent borrower that enables the creditor to legally retain or to sell the collateral in full or partial satisfaction of the debt.

[10] *Bankruptcy* is the legal status of being insolvent or unable to pay debts. Bankruptcy proceedings are legal proceedings in which a bankruptcy court or similar tribunal takes over the assets of the debtor and appoints a receiver or trustee to administer them. Unsecured creditors may also be able to initiate bankruptcy proceedings, but are less sure of compensation than the secured creditor.

[11] A related question is whether the legal framework is sufficiently robust to enable the creditor to enforce his rights against the borrower. Where creditors' rights are weak or difficult to enforce, this consideration becomes part of the credit decision-making process.

[12] Roger H. Hale, *Credit Analysis: A Complete Guide* (New York: John Wiley & Son's 1983, 1989). The traditional reliance on collateral has given rise to the term "pawnshop mentality" to refer to bankers who are incapable or unwilling to perform credit analysis of their customers and lend primarily on the value of collateral pledged. See for example Szu-yin Ho and Jih-chu Lee, *The Political Economy of Local Banking in Taiwan* (Taipei, Taiwan: NPF Research Report, National Policy Foundation, December 10, 2001). "Because of the pawnshop mentality and practices in banking institutions, the SMEs are not considered good customers for loans," http://old.npf.org.tw/english/Publication/FM/FM-R-090-069.htm. *SME* is an acronym for *small-* and *medium-size enterprise.* Murphy, referring to banking practice in Japan in the 1980s, observed that "Japanese banks rarely extend domestic loans of any but the shortest maturity without collateral" (*Real Price*, 49).



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## COLLATERAL AND OTHER CREDIT RISK MITIGANTS

Credit risk mitigants are devices such as collateral, pledges, insurance, or guarantees that may be used to reduce the credit risk exposure to which a lender or creditor would otherwise be subject. The purpose of credit risk mitigants is partially or totally to ameliorate a borrower's lack of intrinsic creditworthiness and thereby reduce the credit risk to the lender, or to justify advancing a larger sum than otherwise would be contemplated. For instance, a lender may require a guarantee where the borrower is comparatively new or lacks detailed financial statements but the guarantor is a well-established enterprise rated by the major external agencies. In the past, these mechanisms were frequently used to reduce or eliminate the need for the credit analysis of a prospective borrower by substituting conservatively valued collateral or the creditworthiness of an acceptable guarantor for the primary borrower.

In modern financial markets, collateral and guarantees, rather than being substitutes for inadequate stand-alone creditworthiness, may actually be a requisite and integral element of the contemplated transaction. Their essential function is unchanged, but instead of remedying a deficiency, they are used to increase creditworthiness to give the transaction certain predetermined credit characteristics. In these circumstances, rather than eliminating the need for credit analysis, consideration of credit risk mitigants supplements, and sometimes complicates it. Real-life credit analysis consequently requires an integrated approach to the credit decision, and typically requires some degree of analysis of both the primary borrower and of the impact of any applicable credit risk mitigants.

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or has a comparable level of creditworthiness but is easier to analyze. Often, there will be some relationship between the guarantor and the party on whose behalf the guarantee is provided. For example, a father may guarantee a finance company's loan to his son[13] for the purchase of a car. Likewise, a parent company may guarantee a subsidiary's loan from a bank to fund the purchase of new premises.

Where a guarantee is provided, the questions posed with reference to the prospective borrower must be asked again in respect of the prospective guarantor: "Will the prospective guarantor be both willing to repay the obligation and have the capacity to repay it?" These questions are summarized in Table 1-1.

## Significance of Credit Risk Mitigants

In view of the benefits of using collateral and guarantees to avoid the sometimes thorny task of performing an effective financial analysis,[14] banks and other institutional lenders traditionally have placed primary emphasis on these credit risk mitigants, and other comparable mechanisms such as *joint and several liability*[15] when allocating credit.[16] For this reason, *secured lending*, which refers to the use of credit risk mitigants to secure a financial obligation as discussed, remains a favored method of providing financing.

In countries where financial disclosure is poor or the requisite analytical skills are lacking, credit risk mitigants circumvent some of the difficulties involved in performing an effective credit evaluation. In developed markets, more sophisticated approaches to secured lending such as *repo finance* and *securities lending*[17] have also grown increasingly popular. In these markets, however, the use of credit risk mitigants is often driven by the desire to facilitate

[13] Typically, in this situation, the loan would be advanced by an auto manufacturer's finance subsidiary.

[14] *Financial analysis* is the process of arriving at conclusions concerning an entity's financial condition or performance through the examination of its financial statements, such as its balance sheet and income statement. Financial analysis encompasses a wide range of activities that may be employed for internal management purposes (e.g., to determine which business lines are most profitable) or for external evaluation purposes (e.g., equity or credit analysis).

[15] *Joint and several liability* is a legal concept under which each of the parties to an obligation is liable to the full extent of the amount outstanding. In other words, where there are multiple obligors, the obligee (creditor) is entitled to demand full repayment of the entire outstanding obligation from any and all of the obligors (borrowers).

[16] As well as having an impact on whether to advance funds, the use of collateral, guarantees, and other credit risk mitigants may also serve to increase the amount of funds the lender is willing to put at risk.

[17] *Repo finance* refers to the use of repurchase agreements and reverse repurchase agreements to facilitate mainly short-term collateralized borrowings and advances. Securities lending transactions are similar to repo transactions.



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**TABLE 1-1** Key Credit Questions

| | | Binary (Yes/No) | Probability |
|---|---|---|---|
| Willingness to pay | Primary Subject of Analysis (e.g., borrower) | Will the prospective borrower be willing to repay the funds? | What is the likelihood that a borrower will perform its financial obligations in accordance with their terms? |
| Capacity to pay | | Will the prospective borrower be able to repay the funds? | |
| Collateral | Secondary Subject of Analysis (Credit risk mitigants) | Will the collateral provided by the prospective borrower or the guarantees given by a third party be sufficient to secure repayment? | What is the likelihood that the collateral provided by the prospective borrower or the guarantees given by a third party will be sufficient to secure repayment? |
| Guarantees | | Will the prospective guarantor be willing to repay the obligation as well as have the capacity to repay it? | What is the likelihood that the prospective guarantor will be willing to repay the obligation as well as have the capacity to repay it? |

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investment transactions or to structure credit risks to meet the needs of the parties to the transaction rather than to avoid the process of credit analysis.

With the evolution of financial systems, credit analysis has become increasingly important and more refined. For the moment, though, our focus is upon credit evaluation in its more basic and customary form.

## WILLINGNESS TO PAY

Willingness to pay is, of course, a subjective attribute that can be ascertained to a degree from the borrower's reputation and apparent character. Assuming free will,[18] it is also essentially unknowable in advance, even perhaps to the borrower. From the perspective of the lender or credit analyst, the evaluation is therefore necessarily a *qualitative* one that takes into account information gleaned from a variety of sources, including, where possible, face-to-face meetings that are a customary part of the process of *due diligence*.[19]

The old-fashioned provincial banker who was familiar with local business conditions and prospective borrowers, like the fictional character described earlier, had less need for formal credit analysis. Instead, the intuitive judgment that came from an in-depth knowledge of a community and its members was an invaluable attribute in the banking industry. The traditional banker knew with whom he was dealing (or thought he did), either locally with his

[18] *Free will* has been defined as the power of making choices unconstrained by external agencies, wordnetweb.princeton.edu/perl/webwn. If so defined—that is, meaning having the freedom to choose a course of action in the moment—it is by definition not predetermined, and therefore the actions of an entity having free will cannot be 100 percent predictable. This is not to say, however, that predictive—if not determinative—factors cannot be identified, and that the probability of various scenarios unfolding cannot be estimated, especially when the number of transactions involved is large. Indeed, much of credit risk evaluation is underpinned by implicit or explicit statistical expectations based on the occurrence of a large number of transactions.

[19] *Due diligence* means the review of accounts, documentation, and related written materials, together with interviews with an entity's principals and key personnel, for the purpose of supporting a professional assessment concerning the entity. A due diligence investigation is typically performed in connection with a prospective transaction. So a law firm would likely perform a due diligence investigation before rendering of a legal opinion concerning an anticipated transaction. So, too, will a rating agency undertake a due diligence review before assigning a rating to an issuer.



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customers or at a distance with *correspondent banks*[20] that he trusted. Walter Bagehot, the nineteenth-century British economic commentator put it well:

> A banker who lives in the district, who has always lived there, whose whole mind is a history of the district and its changes, is easily able to lend money there. But a manager deputed by a central establishment does so with difficulty. The worst people will come to him and ask for loans. His ignorance is a mark for all the shrewd and crafty people thereabouts.[21]

In general, modern credit analysis still takes account of willingness to pay, and in doing so maintains an unbroken link with its past. It is still up to one or more individuals to decide whether to extend or to repay a debt, and manuals on banking and credit analysis as a rule make some mention of the importance of taking account of a prospective borrower's character.[22]

## Indicators of Willingness

Willingness to pay, though real, is difficult to assess. Ultimately, judgments about this attribute, and the criteria on which they are based, are highly subjective in nature.

## Character and Reputation

First-hand awareness of a prospective borrower's character affords at least a stepping-stone on which to base a credit decision. Where direct familiarity is lacking, a sense of the borrower's reputation provides an alternative footing upon which to ascertain the obligor's disposition to make good on a promise. Reliance on reputation can be perilous, however, since a dependence upon second-hand information can easily descend into so-called *name lending.*[23] Name lending can be defined as the practice of lending to customers based on their perceived status within the business community instead of on the basis of facts and sound conclusions derived from a rigorous analysis of the prospective borrowers' actual capacity to service additional debt.

## Credit Record

Although far more data is available today than a century ago, assessing a borrower's integrity and commitment to perform an obligation still requires making unverifiable, even intuitive, judgments. Rather than put a foot wrong into a miasma of imponderables, creditors have long taken a degree of comfort not only in collateral and guarantees, but also in a borrower's verifiable history of meeting its obligations.

As compared with the prospective borrower who remains an unknown quantity, a track record of borrowing funds and repaying them suggests that the same pattern of repayment will continue in the future.[24] If available, a borrower's

[20] A *correspondent bank* is a bank that has a relationship with a foreign banking institution for which it performs services in the correspondent bank's home market. Since few, if any banks, can feasibly maintain branches in all countries of the world, correspondent banking relationships enable institutions without branches or offices in a given jurisdiction to act on a global basis on behalf of such institutions' clients. Typical services provided by a correspondent bank for a foreign institution include check clearing, funds transfers, and the settlement of transactions, acting as a deposit or collection agent for the foreign bank, and participating in documentary letter of credit transactions.

[21] *Lombard Street*, note 2 supra, quoted in Martin Mayer, *The Bankers: The Next Generation* (Penguin, 1996), 10. The quotation comes from Chapter 3 of the book, entitled "How Lombard Street Came to Exist, and Why It Assumed Its Present Form," and the passage discusses the evolution of commercial banks from institutions reliant on note-issuance to those dependent upon the acceptance of deposits. Note that a leading text book on bank management also pays homage to the axiom that bankers understand their own geographic franchise best and "are more apt to misjudge the quality of loans originating outside [it]. . . . [and] loan officers will be less alert to the economic deterioration of communities outside their trade areas." George H. Hempel, Donald G. Simonson, and A. Coleman, *Bank Management: Text and Cases*, 4th ed. (hereafter *Bank Management*) (New York: John Wiley & Sons, 1994), 377.

[22] For example, *Bank Management*, note 21 supra, observes that there is a consensus among bankers that "the paramount factor in a successful loan is the honesty and goodwill of the borrower," and rates a borrower's character as one of the four fundamental credit criteria to be considered, together with the purpose of the funds, and the primary and secondary sources of loan repayment. In a specialist book focused on emerging markets, *character* is one of five "Cs" of credit, along with capacity, capital, collateral, and conditions. Waymond A. Grier, *The Asiamoney Guide to Credit Analysis in Emerging Markets* (Hong Kong: Asia Law & Practice, 1995), 11.

[23] Ironically, *name lending* is also called "character lending." Distinct from this phenomenon is *related-party lending*, which means advancing funds to a family member of a bank owner or officer, or to another with whom the owner or officer has a personal or business relationship separate from those arising from his or her capacity as a shareholder or as an employee of the bank.

[24] It should be borne in mind that whether relying on first-hand knowledge, reputation, or the borrower's credit history, the analytical distinction between *willingness* to pay and *capacity* to pay is easily blurred. In discussing character, *Bank Management* distinguishes among fraudulent intent, moral failings, and other deficiencies, such as lack of intelligence or management skills, some of which might just as easily come under the heading of *management assessment.* Ultimately, the creditor is only concerned whether the borrower is good for the funds "entrusted" to him, and as a practical matter there is little to be gained for this purpose in attempting to parse between how much this belief rests on willingness to pay and how much it rests upon capacity to pay.

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payment record, provided for example through a credit bureau, can be an invaluable resource for a creditor. Of course, while the past provides some reassurance of future willingness to pay, here as elsewhere, it cannot be extrapolated into the future with certainty in any individual case.[25]

## Creditors' Rights and the Legal System

While the ability to make the requisite intuitive judgments concerning willingness to pay probably comes more easily to some than to others, and no doubt may be honed with experience, perhaps fortunately it has become less important in the credit decision-making process.[26] The concept of a *moral obligation*[27] to repay a debt—which perhaps in the past arguably bolstered the will of the faltering borrower to perform his obligation in full—has been to a large extent displaced in contemporary commerce by legal rather than ethical norms.

It is logical to rank capacity to pay as more important than willingness, since willingness alone is of little value where capacity is absent. Capacity without willingness, however, can be overcome to a large degree through an effective legal system.[28] The stronger and more effectual the legal infrastructure, the better able a creditor is to enforce a judgment against a borrower.[29] Prompt court decisions backed by the threat of the seizure of possessions or other means through the arm of the state will tend to predispose the nonperforming debtor to fulfill its obligations. A borrower who *can* pay but *will not*, is only able to maintain such a position in a legal regime that is ineffective or corrupt, or very strongly favors debtors over creditors.

So as legal systems have developed—along with the evolution of financial analytical techniques and data collection and distribution systems—the attribute of *willingness* to repay has been increasingly overshadowed in importance by the attribute of *capacity* to repay. It follows that the more a legal system exhibits creditor-friendly characteristics—combined with the other critical attributes of integrity, efficiency, and judges' understanding of commercial requirements—the less the lender needs to rely upon the borrower's willingness to pay, and the more important the capacity to repay becomes. The development of capable legal systems has therefore increased the importance of financial analysis and as a prerequisite to it, financial disclosure. Overall, the evolution of more robust and efficient legal systems has provided a net benefit to creditors.[30]

[25] Where, however, there exist a large number of recorded transactions, stronger correlations may be drawn between the borrower's track record and future behavior, allowing the probability of default to be better predicted. This, of course, increases a bank's ability to manage risk, as compared with other entities that engage in comparatively few credit transactions and provides banks with an essential competitive advantage in this regard.

[26] The value of such experience comes not only from the bank officer's having reviewed a greater variety of credit exposures, but also from having gone through an entire business cycle and seen each of its phases and corresponding conditions. As with the credit analysis of large corporate entities, in the credit analysis of (rather than by) financial institutions, the criterion of character tends to be given somewhat less emphasis than is the case in respect to individuals and small businesses. As various financial scandals have shown, however, this reduced emphasis on character is not necessarily justified.

[27] The term *moral obligation* is used here to distinguish it from a legally enforceable obligation. A legal obligation may also represent a moral obligation, but a moral obligation does not necessarily give rise to a legal one.

[28] While full recovery may nonetheless still be impossible, depending upon the borrower's access to funds and the worth of the collateral securing the loan, partial recovery is generally more likely when creditors' rights are strong. The effectiveness of a legal system encompasses many facets, including the cost and time required to obtain legal redress, the consistency and fairness of legal decisions, and the ability to enforce judicial decisions rendered. It may be added that the development of local credit reporting systems also may affect a borrower's willingness to fulfill financial obligations since a borrower may wish to avoid the detrimental effects associated with being tagged as a less than prime credit.

[29] In this chapter, the terms and phrases such as *legal efficiency* and *quality of the legal infrastructure* are used more or less synonymously to refer to the ability of a legal system to enforce property rights and creditors' rights fairly and reliably, as well as in a reasonably timely and cost-effective manner. In a scholarly context, these terms are also used to refer to the ability of legal institutions to reduce "idiosyncratic risk" to entrepreneurs and to prevent the exploitation of outside investors from insiders by protecting their property rights in respect of invested funds. See for example Luc Laeven, "The Quality of the Legal System, Firm Ownership, and Firm Size," presentation at the Stanford Center for International Development, Stanford University, Palo Alto, California, November 11, 2004.

[30] It is apparent that there is almost always a risk that a credit transaction favoring the creditor may not be enforced. This risk is often subsumed under the broader rubric of *legal risk.* Legal risk may be defined generally as a category of operational risk or event risk that may arise from a variety of causes, which insofar as it affects credit risk becomes a proper concern of the credit analyst. Types of legal risk include (1) an adverse change in law or regulation; (2) the risk of being a defendant in time-consuming or costly litigation; (3) the risk of an arbitrary, discriminatory, or unexpected adverse legal or regulatory decision; (4) the risk that the bank's rights as creditor will not be effectively enforced; (5) the risk of ineffective bank supervision; or (6) the risk of penalties or adverse consequences incurred as a result of inadvertent errors in documentation. Note that these subcategories are not necessarily discrete, and may overlap with each other or with other risk classifications.



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## CREDIT ANALYSIS IN EMERGING MARKETS: THE IMPORTANCE OF THE LEGAL SYSTEM

Weak legal and regulatory infrastructure and concomitant doubts concerning the fair and timely enforcement of creditors' rights mean that credit analysis in so-called *emerging markets*[31] is often more subjective than in developed markets. Due consideration must be given in these jurisdictions not only to a prospective borrower's willingness to pay, but equally to the quality of the legal system. Since, as a practical matter, willingness to pay is inextricably linked to the variables that may affect the lender's ability to coerce payment through legal redress, it is useful to consider, as part of the analytical process, the overall effectiveness and creditor-friendliness of a country's legal infrastructure. Like the evaluation of an individual borrower's willingness to pay, an evaluation of the quality of a legal system and the strength of a creditor's rights is a highly qualitative endeavor.

Despite the not inconspicuous inadequacies in the legal frameworks of the countries in which they extend credit, bankers during periods of economic expansion have time and again paid insufficient attention to prospective problems they might confront when a boom turns to bust. Banks have faced criticism for placing an undue reliance upon expectations of government support or, where the government itself is vulnerable to difficulties, upon the International Monetary Fund (IMF). Believing that the IMF would stand ready to provide aid to the governments concerned and thereby indirectly to the borrowers and to their creditors, it has been asserted that banks have engaged in imprudent lending. Insofar as such reliance has occurred, it has arguably been accompanied by a degree of obliviousness on the part of creditors to the difficulties involved in enforcing their rights through legal action.[32]

Willingness to pay, however, remains a more critical criterion in less-developed markets, where the quality of the legal framework may be lacking. In these instances, the efficacy of the legal system in protecting creditors' rights also emerges as an important criterion in the analytical process.[33]

While the quality of a country's legal system is a real and significant attribute, measuring it is no simple task. Traditionally, *sovereign risk ratings* functioned as a proxy for, among other things, the legal risk associated with particular geographic markets. Countries with low sovereign ratings were often implicitly assumed to be subject to a greater degree of legal risk, and vice versa.

In the past 15 years, however, surveys have been conducted in an attempt systematically to grade, if not measure, comparative legal risk. Although by and large these studies have been initiated for purposes other than credit analysis—to assess a country's investment climate, for instance—they would seem to have some application to the evaluation of credit risk. Table 1-2 shows the scores under such an index of rule of law. Some banks have used one or more similar surveys, sometimes together with other criteria, to generate internal creditors' rights ratings for the jurisdictions in which they operate or in which they contemplate credit exposure.

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[31] Coined in 1981 by Antoine W. van Agtmael, an employee of the International Finance Corporation, an affiliate of the World Bank, the term *emerging market* is broadly synonymous with the terms *less-developed country* (LDC) or *developing country*, but generally has a more positive connotation suggesting that the country is taking steps to reform its economy and increase growth with aspirations of joining the world's developed nations (i.e., those characterized by high levels of per capita income among various relevant indicia). Leading emerging markets at present include, among others, the following countries: China, India, Malaysia, Indonesia, Turkey, Mexico, Brazil, Chile, Thailand, Russia, Poland, the Czech Republic, Egypt, and South Africa. Somewhat more developed countries, such as South Korea, are sometimes referred to as *NICs*, or *newly industrialized countries.* Somewhat less-developed countries are sometimes referred to anecdotally as *subemerging markets*, a term that is somewhat pejorative in character.

[32] This is an illustration of the problem of *moral hazard*.

[33] Regrettably for lenders in emerging markets, effective protection of creditors' rights is not the norm. As was seen in the aftermath of the Asian financial crisis during 1997–1998, the legal systems in some countries were demonstrably lacking in this regard. Reforms that have been implemented, such as the revised bankruptcy law enacted in Thailand in 1999, have gone some distance toward remedying these deficiencies. The efficacy of new statutes is, however, dependent upon a host of factors, including the attitudes, expertise, and experience of all participants in the judicial process. In Thailand and Indonesia, as well as in other comparable jurisdictions where legal reforms have been implemented, it can be expected that it will take some years before changes are thoroughly manifested at the day-to-day level. Similarly, the debt moratorium and emergency laws enacted in Argentina in 2001 and 2002 curtailed creditors' rights in a substantial way. Incidentally, in June 2010 in Iceland, not exactly an emerging market, the Supreme Court ruled that some loans indexed to foreign currency rates were illegal, shifting the currency losses from borrowers to lenders. Similar decisions may yet be taken in Hungary or in Greece.



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**TABLE 1-2** Rule of Law Index: Selected Countries 2010

| Country | Score | Country | Score |
|---|---|---|---|
| Finland | 1.97 | French Guiana | 1.18 |
| Sweden | 1.95 | American Samoa | 1.16 |
| Norway | 1.93 | Bermuda | 1.16 |
| Denmark | 1.88 | Guam | 1.16 |
| New Zealand | 1.86 | Estonia | 1.15 |
| Luxembourg | 1.82 | Portugal | 1.04 |
| Netherlands | 1.81 | Barbados | 1.04 |
| Austria | 1.80 | Slovenia | 1.02 |
| Canada | 1.79 | Tuvalu | 1.02 |
| Switzerland | 1.78 | Taiwan, China | 1.01 |
| Australia | 1.77 | Korea, South | 0.99 |
| United Kingdom | 1.77 | Antigua and Barbuda | 0.98 |
| Ireland | 1.76 | Czech Republic | 0.95 |
| Greenland | 1.72 | Monaco | 0.90 |
| Singapore | 1.69 | San Marino | 0.90 |
| Iceland | 1.69 | Martinique | 0.89 |
| Germany | 1.63 | Netherlands Antilles | 0.89 |
| Liechtenstein | 1.62 | Reunion | 0.89 |
| United States | 1.58 | Virgin Islands (U.S.) | 0.89 |
| Hong Kong SAR, China | 1.56 | Cayman Islands | 0.89 |
| France | 1.52 | Israel | 0.88 |
| Malta | 1.48 | Qatar | 0.87 |
| Anguilla | 1.42 | St. Vincent and the Grenadines | 0.86 |
| Aruba | 1.42 | Mauritius | 0.84 |
| Belgium | 1.40 | St. Lucia | 0.82 |
| Japan | 1.31 | Latvia | 0.82 |
| Chile | 1.29 | Brunei | 0.80 |
| Andorra | 1.23 | Hungary | 0.78 |
| Spain | 1.19 | Puerto Rico | 0.77 |
| Cyprus | 1.19 | Lithuania | 0.76 |

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| Country | Score | Country | Score |
|---|---|---|---|
| Palau | 0.74 | Kiribati | 0.07 |
| Uruguay | 0.72 | Romania | 0.05 |
| St. Kitts and Nevis | 0.71 | Seychelles | 0.02 |
| Macao SAR, China | 0.71 | Brazil | 0.00 |
| Dominica | 0.69 | Montenegro | −0.02 |
| Poland | 0.69 | India | −0.06 |
| Bahamas | 0.68 | Ghana | −0.07 |
| Oman | 0.67 | Micronesia | −0.08 |
| Botswana | 0.66 | Bulgaria | −0.08 |
| Samoa | 0.65 | Sri Lanka | −0.09 |
| Greece | 0.62 | Suriname | −0.09 |
| Slovakia | 0.58 | Egypt | −0.11 |
| Kuwait | 0.54 | Panama | −0.13 |
| Malaysia | 0.51 | Malawi | −0.14 |
| Costa Rica | 0.50 | Morocco | −0.19 |
| Bahrain | 0.45 | Thailand | −0.20 |
| Cape Verde | 0.42 | West Bank Gaza | −0.20 |
| Nauru | 0.41 | Georgia | −0.21 |
| United Arab Emirates | 0.39 | Burkina Faso | −0.21 |
| Italy | 0.38 | Trinidad and Tobago | −0.22 |
| Vanuatu | 0.25 | Marshall Islands | −0.27 |
| Namibia | 0.23 | Macedonia | −0.29 |
| Jordan | 0.22 | Lesotho | −0.30 |
| Croatia | 0.19 | Rwanda | −0.31 |
| Saudi Arabia | 0.16 | Maldives | −0.33 |
| Grenada | 0.11 | Colombia | −0.33 |
| Tunisia | 0.11 | China | −0.35 |
| Bhutan | 0.11 | Bosnia-Herzegovina | −0.36 |
| Turkey | 0.10 | Belize | −0.36 |
| South Africa | 0.10 | Serbia | −0.39 |
| Tonga | 0.09 | Moldova | −0.40 |

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**TABLE 1-2** Continued

| Country | Score | Country | Score |
|---|---|---|---|
| Uganda | −0.40 | Ethiopia | −0.76 |
| Senegal | −0.41 | Algeria | −0.76 |
| Mongolia | −0.43 | Bangladesh | −0.77 |
| Albania | −0.44 | Russia | −0.78 |
| Mali | −0.46 | Pakistan | −0.79 |
| Armenia | −0.47 | Ukraine | −0.80 |
| Guyana | −0.48 | Dominican Republic | −0.81 |
| Vietnam | −0.48 | Nicaragua | −0.83 |
| Zambia | −0.49 | Madagascar | −0.84 |
| Swaziland | −0.50 | Honduras | −0.87 |
| Jamaica | −0.50 | El Salvador | −0.87 |
| Mozambique | −0.50 | Mauritania | −0.88 |
| Tanzania | −0.51 | Azerbaijan | −0.88 |
| Gambia | −0.51 | Laos | −0.90 |
| Gabon | −0.51 | Cook Islands | −0.90 |
| Syria | −0.54 | Iran | −0.90 |
| Philippines | −0.54 | Fiji | −0.90 |
| Cuba | −0.55 | Paraguay | −0.92 |
| Mexico | −0.56 | Togo | −0.92 |
| Niger | −0.57 | Papua New Guinea | −0.93 |
| Argentina | −0.58 | Sierra Leone | −0.94 |
| Peru | −0.61 | Libya | −0.98 |
| Kazakhstan | −0.62 | Liberia | −1.01 |
| Indonesia | −0.63 | Kenya | −1.01 |
| Kosovo | −0.64 | Nepal | −1.02 |
| Lebanon | −0.66 | Guatemala | −1.04 |
| São Tomé and Principe | −0.69 | Cameroon | −1.04 |
| Solomon Islands | −0.70 | Belarus | −1.05 |
| Djibouti | −0.71 | Yemen | −1.05 |
| Niue | −0.72 | Comoros | −1.06 |
| Benin | −0.73 | Bolivia | −1.06 |

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| Country | Score | Country | Score |
|---|---|---|---|
| Cambodia | −1.09 | Sudan | −1.32 |
| Congo | −1.13 | Guinea-Bissau | −1.35 |
| Ecuador | −1.17 | Haiti | −1.35 |
| Tajikistan | −1.20 | Uzbekistan | −1.37 |
| Nigeria | −1.21 | Turkmenistan | −1.46 |
| Timor-Leste | −1.21 | Chad | −1.50 |
| Burundi | −1.21 | Myanmar | −1.50 |
| Côte d'Ivoire | −1.22 | Guinea | −1.51 |
| Angola | −1.24 | Congo, Democratic Republic | −1.61 |
| Equatorial Guinea | −1.26 | Iraq | −1.62 |
| Eritrea | −1.29 | Venezuela | −1.64 |
| Kyrgyzstan | −1.29 | Zimbabwe | −1.80 |
| Korea, North | −1.30 | Afghanistan | −1.90 |
| Central African Republic | −1.30 | Somalia | −2.43 |

*Source:* World Bank.

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It is almost invariably the case that the costs of legal services are an important variable to be considered in any decision regarding the recovery of money owed. A robust legal system is not necessarily a cost-effective one, since the expenses required to enforce a creditor's rights are rarely insignificant. While a modicum of efficiency may exist, the costs of legal actions, including the time spent pursuing them, may well exceed the benefits. It therefore may not pay to take legal action against a delinquent borrower. This is particularly the case for comparatively small advances. As a result, even where creditors' rights are strictly enforced, willingness to pay ought never to be entirely ignored as an element of credit analysis.

## EVALUATING THE CAPACITY TO REPAY: SCIENCE OR ART?

Compared with *willingness* to pay, the evaluation of *capacity* to pay lends itself more readily to *quantitative* measurement. So the application of financial analysis will generally go far in revealing whether the borrower will have the ability to fulfill outstanding obligations as they come due. Evaluating the capability of an entity to perform its financial obligations through a close examination of numerical data derived from its most recent and past financial statements forms the core of *credit analysis.*

### The Limitations of Quantitative Methods

While an essential element of credit evaluation, the use of financial analysis for this purpose is subject to serious limitations. These include:

- The historical character of financial data.
- The difficulty of making reasonably accurate financial projections based upon such data.
- The inevitable gap between financial reporting and financial reality.

### Historical Character of Financial Data

The first and most obvious limitation is that financial statements are invariably historical in scope, covering as they do past fiscal reporting periods, and are therefore



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never entirely up to date. Because the past cannot be extrapolated into the future with any certainty, except perhaps in cases of clear *insolvency* and *illiquidity*, the estimation of capacity remains just that: an estimate.

Even if financial reports are comparatively recent, or forward looking, the preceding difficulty is not surmounted. Accurate financial forecasting is notoriously problematic, and, no matter how sophisticated, financial projections are highly vulnerable to errors and distortion. Small differences at the outset can engender an enormous range of values over time.

## Financial Reporting Is Not Financial Reality

Perhaps the most significant limitation arises from the fact that financial reporting is an inevitably imperfect attempt to map an underlying economic reality into a usable but highly abbreviated condensed report. As with attempts to map a large spherical surface onto a flat projection, some degree of deformation is unavoidable, while the very process of distilling raw data into a work product small enough to be usable requires that some data be selected and other data be omitted. In short, not only do financial statements intrinsically suffer from some degree of distortion and omission, these deficiencies are also apt to be aggravated in practice.

First, the rules of financial accounting and reporting are shaped by people and institutions having differing perspectives and interests. Influences resulting from that divergence are apt to aggravate these innate deficiencies. The rules themselves are almost always the product of compromises by committee that are, at heart, political in nature.

Second, the difficulty of making rules to cover every conceivable situation means that, in practice, companies are frequently afforded a great deal of discretion in determining how various accounting items are treated. At best, such leeway may only potentially result in inaccurate comparisons; at worst, this necessary flexibility in interpretation and classification may be used to further deception or fraud.

Finally, even the most accurate financial statements must be interpreted. In this context too, differing vantage points, experience, and analytical skill levels may result in a range of conclusions from the same data. For all these reasons, it should be apparent that even the seemingly objective evaluation of financial capacity retains a significant qualitative, and therefore subjective, component. While acknowledging both its limitations and subjective element, financial analysis remains at the core of effective credit analysis. The associated techniques serve as essential and invaluable tools for drawing conclusions about a company's creditworthiness, and the credit risk associated with its obligations.

It is, nevertheless, crucial not to place too much faith in the quantitative methods of financial analysis in credit risk assessment, nor to believe that quantitative data or conclusions drawn from such data necessarily represent an objective truth. No matter how sophisticated, when applied for the purpose of the evaluation of credit risk, these techniques must remain imperfect tools that seek to predict an unknowable future.

## Quantitative and Qualitative Elements

Given these shortcomings, the softer more qualitative aspects of the analytical process should not be given short shrift. Notably, an evaluation of management—including its competence, motivation, and incentives—as well as the plausibility and coherence of its strategy remains an important element of credit analysis of both *nonfinancial and financial companies.*[34] Indeed, as suggested in the previous subsection, not only is credit analysis both qualitative and quantitative in nature, but nearly all of its nominally quantitative aspects also have a significant qualitative element.

While evaluation of willingness to pay and assessment of management competence obviously involve subjective judgments, so too, to a larger degree than is often

> QUANTITATIVE METHODS IN CREDIT ANALYSIS
>
> These remain imperfect tools that aim to predict an unknowable future. Nearly all of the nominally quantitative techniques also have a significant qualitative element. To reach optimal effectiveness, credit analysis must therefore combine the effective use of quantitative tools with sound qualitative judgments.

[34] The term *financial company* is used here to contrast financial intermediaries with nonfinancial enterprises. Not to be confused with the term *finance company, financial company* refers to banks as well as to nonbank financial intermediaries, abbreviated NBFIs.



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recognized, do the presentation and analysis of a firm's financial results. Credit analysis is as much art as it is science, and its successful application relies as much on judgment as it does on mathematics. The best credit analysis is a synthesis of quantitative measures and qualitative judgments. For reasons that will soon become apparent, this is particularly so in regard to financial institution credit analysis.

## Credit Analysis versus Credit Risk Modeling

At this stage, it should be noted that there is an important distinction to be drawn between credit risk analysis, on the one hand, and credit risk modeling and credit risk management, on the other. The process of performing a counterparty credit analysis is quite different from that involved in modeling bank credit risk or in managing credit risk at the enterprise level. Consider, for example, the concept of rating migration risk.

Rating migration risk, while an important factor in modeling and evaluating portfolios of debt securities, is not, however, of concern to the credit analyst performing an evaluation of the kind upon which its rating has been based. It is important to recognize this distinction and to emphasize that the aim of the credit analyst is not to model credit risk, but instead to perform the evaluation that provides one of the requisite inputs to credit

### RATING MIGRATION RISK

Credit risk is defined as the risk of loss arising from default. Of all the credit analyst roles, rating agency analysts probably adhere most closely to that definition in performing their work. Rating agencies are in the financial information business. They do not trade in financial assets. The function of rating analysts is therefore purely to evaluate, through the assignment of rating grades, the relative credit risk of subject exposures. Traditionally, agency ratings assigned to a given issuer represent, in the aggregate, some combination of probability of default and loss-given-default.

However, the fixed income analyst and, on occasion, the counterparty credit analyst, may be concerned with a superficially different form of credit risk that, ironically, can be attributed in part to the rating agencies themselves. The fixed income analyst, especially, is worried not only about the expected loss arising from default, but also about the risk that a company's bonds, or other debt instruments, may be downgraded by an external rating agency. Although rating agencies ostensibly merely provide an opinion as to the degree of default risk, the very act of providing such assessments tends to have an impact on the market.

For example, the downgrade of an issuer's bond rating by one or more external agencies will often result in those bonds having a lower value in the market, even though the actual financial condition of the company and the risk of default may not have altered between the day before the downgrade was announced and the day after. For this reason, this type of credit risk is sometimes distinguished from the credit risk engendered by the possibility of default. It is called downgrade risk, or, more technically, rating migration risk, meaning the risk that the rating of an obligor will change with an adverse effect on the holder of the obligor's securities.

At first glance, downgrade risk might be attributed to the role rating agencies play in the market as arbiters of credit risk. But even if no credit rating agencies existed, a risk akin to rating migration risk would exist: the risk of a change in credit quality. Through the flow of information in the market, any significant change in the credit quality of an issuer or counterparty should ultimately manifest in a change in its credit risk assessment made by market participants. At the same time, the changes in perceived creditworthiness would be reflected in market prices implying a change in risk premium commensurate with the price change. Nevertheless, the risk of a decline in credit quality is at the end of the day only of concern insofar as it increases the risk of default. It can therefore be viewed simply as a different manifestation of default risk rather than constituting a discrete form of risk. Nevertheless, rating migration is used in some credit risk models, as it usefully functions as a proxy for changes in the probability of default over time.

Ideally, downgrade risk should be equivalent to the risk of a decline in credit quality. In practice, however, there will inevitably be gaps between the rating assigned to a credit exposure and its actual quality as the latter improves or declines incrementally over time. What distinguishes the risk of a decline in credit quality from default risk as conventionally perceived is its impact on securities pricing. A decline in credit quality will almost always be reflected in a widening of spreads above the risk-free rate and a decline in the price of the debt securities affected by the decline. Since price risk by definition constitutes market risk, separating the market risk element from the credit risk element in debt pricing is no easy task.



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risk models. Needless to say, it is also one of the requisite inputs to the overall risk management of a banking organization.

## CATEGORIES OF CREDIT ANALYSIS

Until now, we have been looking at the credit decision generally, without reference to the category of borrower. While *capacity* means having access to the necessary funds to repay a given financial obligation, in practice the evaluation of capacity is undertaken with a view to both the type of borrower and the nature of the financial obligation contemplated. Here the focus is on the category of borrower.

Very broadly speaking, credit analysis can be divided into four areas according to borrower type. The four principal categories of borrowers are consumers, nonfinancial companies (corporates), financial companies—of which the most common are banks—and government and government-related entities. The four corresponding areas of credit analysis are listed together with a brief description:

1. Consumer credit analysis is the evaluation of the creditworthiness of individual consumers.
2. Corporate credit analysis is the evaluation of nonfinancial companies, such as manufacturers, and nonfinancial service providers.
3. Financial institution credit analysis is the evaluation of financial companies including banks and nonbank financial institutions (NBFIs), such as insurance companies and investment funds.
4. Sovereign/municipal credit analysis is the evaluation of the credit risk associated with the financial obligations of nations, subnational governments, and public authorities, as well as the impact of such risks on obligations of nonstate entities operating in specific jurisdictions.

While each of these areas of credit assessment shares similarities, there are also significant differences. To analogize to the medical field, *surgeons* might include orthopedic surgeons, heart surgeons, neurosurgeons, and so on. But you would not necessarily go to an orthopedic surgeon for heart surgery or a heart surgeon for brain surgery. Although the primary subject of this chapter is the credit analysis of banks, in describing the context in which this specialist activity takes place, it is worth taking a broad look at the entire field.

> **CONSUMER CREDIT ANALYSIS**
>
> The comparatively small amounts at risk to individual consumers, broad similarities in the relative structure of their financial statements, the large number of transactions involved, and accompanying availability of data allow consumer credit analysis to be substantially automated through the use of credit-scoring models.

To begin, let us consider how one might go about evaluating the capacity of an individual to repay his debts, and then briefly consider the same process in reference to both nonfinancial (i.e., corporate)[35] and financial companies.

### Individual Credit Analysis

In the case of individuals, common sense tells us that their wealth, often measured as *net worth*,[36] would almost certainly be an important measure of capacity to repay a financial obligation. Similarly, the amount of incoming cash at an individual's disposal—either in the form of salary or returns from investments—is plainly a significant attribute as well. Since for most individuals, earnings and cash flow are generally equivalent, *income*[37] and net worth provide the fundamental criteria for measuring their capacity to meet financial obligations.

[35] While banks and other financial institutions are usually organized as corporations, the term *corporate* is frequently used both as an adjective and as a noun to generically refer to *nonfinancial enterprises*, such as manufacturers, wholesalers, and retailers, electrical utilities and service providers, owned by mainly private investors as opposed to those principally owned or controlled by governments or their agencies. The latter would usually fall under the rubric of state-owned enterprises.

[36] *Net worth* may be defined as being equal to assets less liabilities, and is generally synonymous with the following terms which are often used to describe the same concept in relation to companies: equity capital; total equity; net assets; owners' equity; stockholders' equity; shareholders' funds; net asset value; and net tangible assets (net assets less intangible assets such as goodwill). More generally, it may be observed that financial terms are often associated with a plethora of synonyms, while, at the same time, fundamental terms such as *capital* or *nonperforming loans* may have distinctly different meanings depending upon the circumstances.

[37] *Income* is an accounting concept distinct from *cash flow* in that it seeks to match past and future cash flows with the transaction that generated them, rather than classifying such movements strictly on the basis of when—that is, in which financial reporting period—they occurred.

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As is our hypothetical Chloe, on the next page, most individuals are employed by businesses or other enterprises, earn a salary and possibly bonuses or commissions, and typically own assets of a similar type, such as a house, a car, and household furnishings. With some exceptions, cash flow as represented by the individual's salary tends to be fairly regular, as are household expenses. Moreover, unsecured[38] credit exposure to individuals by creditors is generally for relatively small amounts. Unsurprisingly, default by consumers is very often the result of loss of income through unemployment or unexpectedly high expenses, as may occur through sudden and severe illness in the absence of health insurance.

Because the credit analysis of individuals is usually fairly simple in nature, it is amenable to automation and the use of statistical tools to correlate risk to a fairly limited number of variables. Moreover, because the amounts advanced are comparatively small, it is generally not cost-effective to perform a full credit evaluation encompassing a detailed analysis of financial details and a due diligence interview of the individual concerned. Instead, scoring models that take account of various household characteristics such as salary, duration of employment, amount of debt, and so on, are typically used, particularly with respect to unsecured debt (e.g., credit card obligations). Substantial credit exposure by creditors to individual consumers will ordinarily be in the form of secured borrowing, such as *mortgage lending* to fund a house purchase or auto finance to fund a car purchase. In these situations, scoring methodologies are also employed, but may be coupled with a modest amount of manual input and review.

## Evaluating the Financial Condition of Nonfinancial Companies

The process of evaluating the capacity of a firm to meet its financial obligations is similar to that used to assess the capacity of an individual to repay his debts. Generally speaking, however, a business enterprise is more difficult to analyze than an individual. Not only do enterprises vary hugely in the character of their assets, the regularity of their income stream, and the degree to which they are subject to demands for cash, but also the financial structure of firms is almost always more complex than it is for individuals. In addition, the interaction of each of the preceding attributes complicates matters. Finally, the amount of funds at stake is usually significantly higher—and not infrequently far higher—for companies than it is for consumers. As a consequence, the credit analysis of nonfinancial companies tends to be more detailed and more hands-on than consumer credit analysis.

It is both customary and helpful to divide the credit analysis of organizations according to the attributes to be analyzed. As a paradigm, consider the *corporate credit analyst* evaluating credit exposure to a nonfinancial firm, whether in the form of financial obligations in the form of bonds issued by multinational firms or bread-and-butter loans to be made to an industrial or service enterprise. As a rule, the analyst will be particularly concerned with the following criteria, and this will be reflected in the written report that sets forth the conclusions reached:

- The company's *liquidity*
- Its *cash flow* together with
- Its near-term *earnings capacity* and *profitability*
- Its *solvency* or *capital* position

Each of these attributes is relevant also to the analysis of financial companies.

## Evaluating Financial Companies

The elements of credit analysis applicable to banks and other financial companies share many similarities to those applied to nonfinancial enterprises. The attributes of liquidity, solvency, and historical performance mentioned are all highly relevant to financial institutions. As with corporate credit analysis, the quality of management, the state of the economy, and the industry environment are also vital factors in evaluating financial company creditworthiness.

Yet, as the business of financial companies differs in fundamental respects from that of nonfinancial businesses, so too does their analysis. These differences have a substantial impact on how the performance and condition of the former are evaluated. Similarly, how various financial characteristics of banks are measured and the weight given to various categories of their performance contrast in many respects with the manner in which corporates are analyzed.

[38] *Unsecured* means without security such as collateral or guarantees.

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## CASE STUDY: INDIVIDUAL CREDIT ANALYSIS

*Net worth* means an individual's surplus of assets over debts. Consider, for example, a hypothetical 33-year-old woman named Chloe Williams, who owns a small house on the outskirts of a medium-sized city, let us call it Oakport, worth $140,000.[39] There is a remaining mortgage of $100,000 on the house, and Chloe has $10,000 in savings, solely in the form of bank deposits and mutual funds, and no other debts (see Table 1-3).

Leaving aside the value of Chloe's personal property—clothes, jewelry, stereo, computer, motor scooter, for instance—she would have a net worth of $50,000. Chloe's salary is $36,000 per annum after tax. Since her salary is paid in equal and regular installments in arrears (at the end of the relevant period) on the fifteenth and the last day of each month, we can equate her after-tax income with cash flow. Leaving aside nominal interest and dividend income, her total monthly cash flow (see Table 1-4) would be $3,000 per month.

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**TABLE 1-3** Chloe's Net Worth

| **Chloe's Assets** | **$** | **Chloe's Obligations and Equity** | **$** | **Remarks:** |
|---|---|---|---|---|
| Chloe's House<br>Portion of house value STILL owned to bank | 100,000 | Liabilities—mortgage owed to bank (Chloe's mortgage on her house: financial obligation to bank) | 100,000 | *2-bedroom house at 128 Bayview Drive, Current market value: $140,000*<br>*A single major liability—the funds she owes to the bank, which is an obligation secured by her house* |
| Portion of house value NOT owned by bank—*relatively illiquid* | 40,000 | Home equity—unrealized if she sells the house | 40,000 | *Chloe's Net Worth = $50,000* |
| Cash and Securities<br>Owns in full without margin loans—*liquid assets* | 10,000 | Equity in securities—unrealized unless she sells them | 10,000 | |
| | 150,000 | | 150,000 | |

*Notes:* Value of some assets (house, securities) depends on their market value. Traditionally a business would value them at their fair value or cost.

**TABLE 1-4** Chloe's Cash Flow

| | **Annually $** | **Monthly $** |
|---|---|---|
| Chloe's after-tax income | 36,000 | 3,000 |
| Less: Salary applied to living costs and mortgage payment | (26,000) | (2,167) |
| Net cash flow available to service debt | 10,000 | 833 |

### Net Cash Flow

Net cash flow[40] is what remains after taking account of Chloe's other outgoings: utilities, groceries, mortgage payments, and so on.

To analyze Chloe's capacity to repay additional indebtedness, it is therefore reasonable to consider her net worth and income, together with her net cash flow, her track record in meeting obligations, and her level of job security, among other things. That Chloe has an impeccable credit record, has been with her company, an established Fortune 500 corporation for six years, with a steadily increasing salary and significant net worth would typically be viewed by a bank manager as *credit positive.*[41]



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Suffice it to say for the moment that the key areas that a credit analyst will focus on in evaluating a bank include the following:

- *Earnings capacity*—that is, the bank's performance over time, particularly its ability to generate *operating income* and *net income* on a sustained basis and thereby overcome any difficulties it may confront.
- *Liquidity*—that is, the bank's access to cash or cash equivalents to meet current obligations.
- *Capital adequacy* (a term frequently used in the context of financial institutions that is essentially equivalent to *solvency*)—that is, the cushion that the bank's capital affords it against its liabilities to depositors and the bank's creditors.
- *Asset quality*—that is, the likelihood that the loans the bank has extended to its customers will be repaid, taking into account the value and enforceability of collateral provided by them.

Even in this brief list, differences between the key criteria applied to corporate credit analysis and those important in the credit analysis of financial and nonfinancial companies are apparent. They are:

- The importance of asset quality.
- The omission of cash flow as a key indicator.

As with nonfinancial companies, qualitative analysis plays a substantial role, even a more important role, in financial institution credit analysis.

Finally, it should be noted that there is a great deal of diversity among the entities that comprise the financial sector. In this chapter, we focus almost exclusively on banks. They are the most important category of financial institutions and also probably the most numerous. Banking organizations, so defined, nonetheless embrace a wide range of institutions, and the category embraces a number of subcategories, including commercial banks, specialized, wholesale banks, trust banks, development banks, and so on. The number of categories present within a particular country's financial sector depends upon the structure of the industry and the applicable laws governing it. Equally, the terminology used to refer to the different categories of banking institutions is no less diverse, with the relevant statutory definitions for each type varying to a greater or lesser extent from jurisdiction to jurisdiction.

Aside from banks, the remainder of the financial sector is composed of a variety of other types of entities including insurance companies, securities brokerages, and asset managers. Collectively, these entities are referred to as nonbank financial institutions, or as NBFIs. As with the banking industry, the specific composition of the NBFI sector in a particular jurisdiction is influenced by applicable laws, regulations, and government policy.

In these pages, we will focus almost exclusively on commercial banks. An in-depth discussion of the credit analysis of NBFIs is really the subject for another chapter.

## A QUANTITATIVE MEASUREMENT OF CREDIT RISK

So far, our inquiry into the meaning of credit has remained within the confines of tradition. Credit risk has been defined as the likelihood that a borrower will perform a financial obligation according to its terms; or conversely, the probability that it will default on that commitment. The probability that a borrower will default on its obligation to the lender generally equates to the probability that the lender will suffer a loss. As so defined, credit risk and default risk are essentially synonymous. While this has long been a serviceable definition of creditworthiness, developments in the financial services industry and changes in regulation of the sector over the past decade have compelled market participants to revisit the concept.

### Probability of Default

If we think more about the relationship between credit risk and default risk, it becomes apparent that such probability of default (PD), while highly relevant to the

[39] Note that for an individual, net worth is frequently calculated taking account of the market value of key assets such as real property, in contrast to company credit analysis, which, with some exceptions, will value assets at their historical cost.

[40] *Net cash flow* can be defined as cash received less cash paid out for a given financial reporting period.

[41] *Credit positive* means tending to strengthen an entity's perceived creditworthiness, while *credit negative* suggests the opposite. For example, "[The firm's] recent disposal of the fiber-optic network is slightly credit positive." Ivan Lee et. al., *Asia-Pacific-Fixed Income, Asian Debt Perspective–Outlook for 2002* (Hong Kong: Salomon Smith Barney, January–February 2002), 24.

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question what constitutes a "good credit"[42] and what identifies a bad one, is *not* the creditor's *only*, or in some cases even her central concern. Indeed, a default could occur, but should a borrower through its earnest efforts rectify matters promptly—making good on the late payment through the remittance of interest or penalty charges—and resume performance without further breach of the lending agreement, the lender would be made whole and suffer little harm. Certainly, nonpayment for a brief period could cause the lender severe consequential liquidity problems, should it have been relying upon payment to satisfy its own financial obligations, but otherwise the tangible harm would be negligible. Putting aside for a moment the impact of default on a lender's own liquidity, if mere default by a borrower alone is not what truly concerns a creditor, about what then is it really worried?

## Loss Given Default

In addition to the probability of default, the creditor is, or arguably should be, equally concerned with the severity of the default that might be incurred. It is perhaps easier to comprehend retrospectively.

Was it a brief, albeit material default, like that described in the preceding paragraph, that was immediately corrected so that the creditor obtained all the expected benefits of the transaction?

Or was it the type of default in which payment ceases and no further revenue is ever seen by the creditor, resulting in a substantial loss as a result of the transaction?

Clearly, all other things being equal, it is the expectation of the latter that most worries the lender.

*Both* the probability of default and the severity of the loss resulting in the event of default—each of which is conventionally expressed in percentage terms—are crucial in ascertaining the tangible expected loss to the creditor, not to speak of the creditor's justifiable level of apprehension. The loss given default (LGD) encapsulates the likely percentage impact, under default, on the creditor's exposure.

[42] A *good credit* means, of course, a good credit risk; that is, a credit risk where the risk of loss is so minimally low as to be acceptable.

## Exposure at Default

The third variable that must be considered is exposure at default (EAD). EAD may be expressed either in percentage of the nominal amount of the loan (or the limit on a line of a credit) or in absolute terms.

## Expected Loss

The three variables—PD, LGD, and EAD—when multiplied, give us expected loss for a given time horizon.[43]

It is apparent that all three variables are quite easy to calculate after the fact. Examining its entire portfolio over a one-year period, a bank may determine that the PD, adjusted for the size of the exposure, was 5 percent, its historical LGD was 70 percent, and EAD was 80 percent of the potential exposure. Leaving out asset correlations within the loan portfolio and other complexities, expected loss (EL) is simply the product of PD, LGD, and EAD.

EL and its constituents are, however, much more difficult to estimate in advance, although past experience may provide some guidance.

## The Time Horizon

All the foregoing factors are time dependent. The longer the *tenor*[44] of the loan, the more likely it is that a default will occur. EAD and LGD will also change with time, the former increasing as the loan is fully drawn, and decreasing as it is gradually repaid. Similarly, LGD can change over time, depending upon the specific terms of the loan. The nature of the change depends upon the specific terms and structure of the obligation.

## Application of the Concept

To summarize, expected loss is fundamentally dependent upon four variables, with the period often assumed to be one year for the purposes of comparison and analysis. On a portfolio basis, a fifth variable, correlation between credit exposures within a credit portfolio, will also affect *expected loss.*

[43] For simplicity's sake, variables such as the period and correlations within a loan portfolio are omitted in this introductory discussion.

[44] *Tenor* means the term or time to maturity of a credit instrument.

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The PD/LGD/EAD concept just described is extremely valuable as a way to understand and model credit risk.

## Major Bank Failure Is Relatively Rare

While bank credit analysis resembles corporate credit analysis in many respects, it differs in several important ways. The most crucial difference is that, *broadly speaking*, modern banks, in sharp contrast to nonfinancial firms, do not *fail* in normal times. That may seem like a shocking statement. It is an exaggeration, but one that has more truth in it than might first appear, considering that, quite often, weak banks are conveniently merged into other—supposedly stronger—banks. Most bank analysts, if you press them hard enough, will acknowledge the declaration as generally valid, when applied to the more prominent and internationally active institutions that are the subject of the vast majority of credit analyses.

Granted, the present time, in the midst of a substantial financial crisis, does not qualify as normal time. In each of 2009 and 2010, roughly 2 percent of U.S. banks failed, and in 2011, so did roughly 1.2 percent of them. The rate of failure between 1935 and 1940 was about 0.5 percent per year, and it remained below 0.1 percent per year in the 20 years after World War II. Between 2001 and 2008, only 50 banks failed in the United States—half of them in 2008 alone, but that left the overall ratio of that period below 0.1 percent per year.

In the United States alone, other data show that the volume of failures of publicly traded companies numbered in the thousands, with total business bankruptcies in the millions. To be sure, the universe of banks is much smaller than that of nonfinancial companies, but other data confirms that bank collapses are substantially less probable than those of nonfinancial enterprises. This is, of course, not to say that banks *never* fail (recall the foregoing qualification, "broadly speaking"). It is evident the economic history of the past several centuries is littered with the invisible detritus of many long-forgotten banks.

Small local and provincial banks, as well as—mostly in emerging markets—sometimes larger institutions are routinely closed by regulators, or merged or liquidated, or taken over by other healthier institutions, without creating systemic waves.

The proportion of larger banks going into trouble has dramatically increased in the past few years, particularly in the U.K. and in the United States, but also in Europe. The notion of *too big to fail* has always been accepted in the context of each separate market. In November 2011, that notion was extended to include a systemic risk of contagion, with the publication by the Financial Stability Board (FSB) of a list of 29 "systemically important financial institutions" which would be required to hold "additional loss absorption capacity tailored to the impact of their [possible] default." There are of course many more "too big to fail" financial institutions around the world.

The notion of "too small to fail" also exists since it is often cheaper and more expedient—not to mention less embarrassing—for governments to arrange the quiet absorption of a small bank in trouble.

A wide danger zone remains in between those two extremes.

## Bank Insolvency Is Not Bank Failure

The proposition that banks do not fail is, it must be emphasized, an overstatement meant to illustrate a general rule. There is no intent to convey the notion that banks do not become insolvent, for especially with regard to banks (as opposed to ordinary corporations), insolvency and failure are two distinct events. In fact, bank insolvency is far more common, even in the twenty-first century, than many readers are likely to suspect.[45] Equally, insolvent banks can keep going on and on like a notorious advertising icon so long as they have a source of liquidity, such as a central bank as a *lender of last resort.* What *is* meant is that the bankruptcy or collapse of a *major* commercial banking institution that actually results in a significant loss to depositors or creditors is an extremely rare event.[46] Or at least it did remain so until the crisis that started in 2008. For the vast majority of institutions that a bank credit analyst is likely to review, a failure is highly improbable. But because banks are so highly leveraged, these risks, and perhaps more importantly, the risks

[45] Moreover, not all episodes of bank distress reach the newspapers, as problems are remedied by regulators behind the scenes.

[46] In short, while historically a sizable number of banks have closed their doors, and bank defaults and failures are not unknown even today. The types of institutions that do suffer bank collapses are almost always local or provincial, with few, if any, international counterparty relationships.



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that episodes of distress that fall short of failure and may potentially cause harm to investors and counterparties, are of such magnitude that they cannot be ignored.

## Why Bother Performing a Credit Evaluation?

If major bank failures are so rare, why bother performing a credit evaluation? There are several reasons.

- First, evaluating the default risk of an exposure to a particular institution enables the counterparty credit analyst working for a bank to place the risk on a rating scale, which helps in pricing that risk and allocating bank capital.
- Second, even though the risk of default is low, the possibility is a worrisome one to those with credit exposure to such an institution. Consequently, entities with such exposure, including nonfinancial and nonbank financial organizations, as well as investors, both institutional and individuals, have an interest in avoiding default-prone institutions.[47]
- Third, it is not only outright failure that is of concern, but also events short of default can cause harm to counterparties and investors.
- Fourth, globalization has increased the risk of systemic contagion. As a result, the risk on a bank has becomes a twice-remote risk—or in fact a risk compounded many times—on that bank's own risk on other financial institutions with their own risk profile.

## Default as a Benchmark

That bank defaults are rare—barring systemic crises—in today's financial industry does not detract from the conceptual usefulness of the possibility of default in delineating a continuum of risk.[48] The analyst's role is to place the bank under review somewhere on that continuum, taking account of where the subject institution stands in terms of financial strength and the potential for external support. The heaven of pure creditworthiness[49] and the hell of bankruptcy[50] define two poles, somewhere between which a credit evaluation will place the institution in terms of estimated risk of loss. In terms of credit ratings, these poles are roughly demarcated by an AAA rating at one end, and a default rating at the other.

In other words, the potential for failure, if not much more than a remote possibility in most markets, nonetheless allows us to create a sensible definition of credit risk and a spectrum of expected loss probabilities in the form of credit ratings. In turn, these ratings facilitate the external pricing of bank debt and, internally, the allocation of bank capital.

## Pricing of Bank Debt

From a debt investor's perspective, the assessment of bank credit risk distilled into an internal or external rating facilitates the determination of an investment's value, that is, the relationship of risk and reward, and concomitantly its pricing. For example, if hypothetical Dahlia Bank and Fuchsia Bank, both based in the same country, each issue five-year subordinated floating-rate notes paying a semiannual coupon of 6 percent, which is the better investment? Without additional information, they are equally desirable. However, if Dahlia Bank is a weaker credit than Fuchsia Bank, then all other things being equal, Fuchsia Bank is likely to be the better investment since it offers the same rate of return for less risk to the investor.

These evaluations of bank obligations and the information they convey to market participants function to underpin the development and maintenance of efficient money and capital markets. The relationship between credit risk and the return that investors will require to compensate for increasing risk levels can be depicted in a *rating yield curve.* The diagram in Figure 1-1 illustrates a portion of such a curve. Credit risk, as reflected in assigned credit ratings, is shown on the horizontal axis, while the risk premium, described as basis points above the risk-free rate demanded by investors, is shown on the vertical axis. Observe that as of the time captured, for a financial instrument having a rating of BBB, corresponding roughly to a default probability within one year of between

[47] Retail depositors will also be concerned with a bank's possible default, although their deposits are often insured by governmental or industry entities to some extent.

[48] As discussed, credit risk is largely measured in terms of the probability of default, and loss severity (loss given default).

[49] In other words, 0 percent risk of loss, that is, a risk-free investment.

[50] The worst-case scenario refers to an institution in default, subject to liquidation proceedings, in which 100 percent of principal and interest are unrecoverable.



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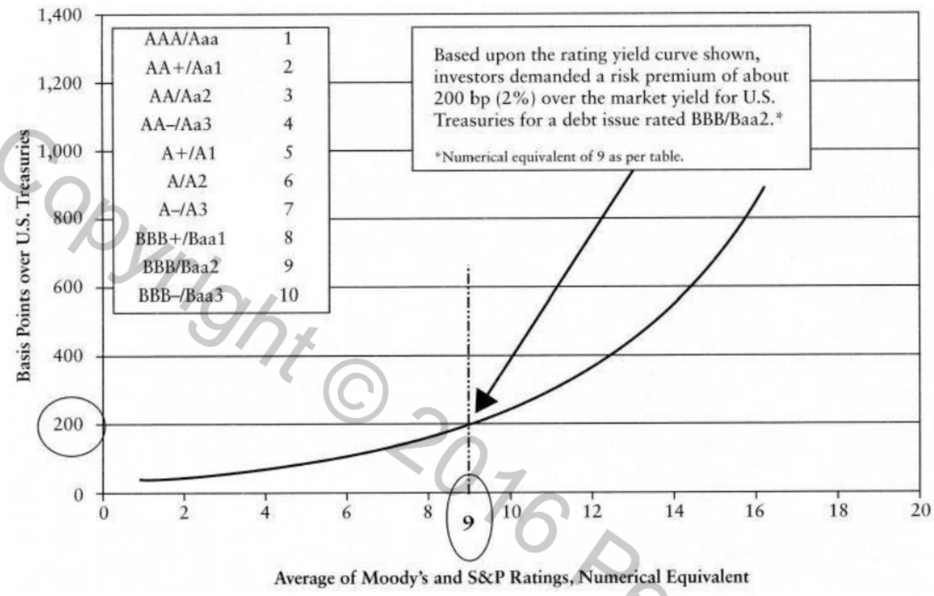


**FIGURE 1-1** External ratings and the rating yield curve.

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0.2 percent and 0.4 percent,[51] investors required a premium of about 200 basis points (bps) or 2 percent yield above the risk-free rate.

## Allocation of Bank Capital

From the counterparty credit analyst's perspective, the same assessment process enables the institution for which she works to better allocate its risks and its capital in a manner that is both prudent and compliant with relevant regulatory prescriptions.[52] For internal risk management purposes, bank analysis facilitates the setting of exposure limits with regard to the advance of funds, exposure to derivatives, and settlement.

## Events Short of Default

The default of an entity to which one has credit exposure is obviously something to be avoided. The risk of default is also useful conceptually to define a spectrum of default risk. But what about events short of default? How do they figure in the calculus of the creditor or investor? As alluded to, a bank does not have to fail for it to cause damage to a counterparty or creditor. A *technical default*, not to speak of a more material one, can have critical consequences. If a company's treasurer, for example, loses access to funds on deposit with a bank even temporarily, this loss of access can have serious knock-on effects, even if all the funds at stake are ultimately repaid.[53] Likewise, if one bank is relying upon another's creditworthiness as part of a larger transaction, the first bank's default, again even if only technical or temporary, can be a grave matter for its counterparty, potentially harming its own credit rating and reputation in the market. In all of the foregoing cases, irrespective of the likelihood of outright bank failure, bank credit analysis provides the means to avoid fragile banks, as well as the tools to steer clear of failure-prone institutions in markets where bank collapses are not so uncommon.

## Banks Are Different

Banks are different in that they are highly regulated and their assessment is intrinsically highly qualitative. In many respects, however, bank credit analysis and corporate credit analysis are more alike than they are dissimilar. Yet there are vital differences in their respective natures that call for separate approaches to their evaluation both in respect to the qualitative and quantitative aspects of credit analysis. Some of these differences relate to the structure of a bank's financial statements as compared with a nonfinancial entity. Others have to do with the role of banks within a jurisdiction's financial system and their impact on the local economy.

The banking sector is among the most tightly regulated of all industries worldwide. This fact alone means that the scope, character, and effectiveness of the regulatory apparatus will inevitably affect the performance and

[51] Such default risk ranges are associated with ratings. In the past, each rating agency defined ratings in vague terms rather than as probabilities of default—other than as ranges of historical observations—and each rating agency would have its own definition. The advent of Basel II has now forced them to map each rating level to a range of probabilities of default.

[52] A discussion of the mechanics of economic capital allocation is unnecessary for the purposes of this chapter.

[53] A decline in the credit quality of the bank has prompted the analyst to seek a reduction in limits for the exposure to the bank.



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financial condition of institutions that come within its ambit. Consequently, consideration of the adverse and beneficial consequences of existing regulations, and proposed or promulgated changes, will necessarily assume a higher profile than is normally the case in connection with nonfinancial companies.

The reason that banks are heavily regulated is in large part attributable to the preeminent role they play within the financial markets in which they operate. As crucial components within a national payment system and the extension of credit within a region or country, their actions and health inevitably have a major impact on the climate of the surrounding economy. Consequently, banks are more important than their apparent size, measured in terms of revenue generation and employment levels, would suggest. It should not be surprising therefore that governments around the world take a keen interest in the health of the banks operating within their borders, and, supervise them to a far greater degree than they do nonfinancial enterprises. In contrast, nonfinancial firms, with a few exceptions, are lightly regulated in most jurisdictions, and governments generally take a hands-off policy toward their activities.

In most contemporary market-driven economies, if an ordinary company fails, it is of no great concern. This is not so in the case of banks. Because they depend on depositor confidence for their survival, and since governments neither want to confront irate depositors, nor more critically, contend with a significant number of banks unable to function as payment and credit conduits, deposit-taking institutions are rarely left to fend for themselves and go bust without a passing thought. Even where *deposit insurance* exists and depositors remain pacified, the failure of a single critical financial institution may be plausibly viewed by policymakers as likely to have a detrimental impact on the health of the regional or national financial system. Moreover, the costs of repairing a banking crisis typically far outweigh the costs of taking prudent measures to prevent one. Governments therefore actively monitor, regulate, and—in light of the importance of banks to their respective economies—ultimately function as lenders of last resort through the national central bank, or an equivalent agency.

Owing to the privileged position that banks commonly enjoy, their credit analysis must give due consideration to an institution's role within the relevant financial system. Its position will affect the analyst's assessment concerning the probability, and degree, of support that may be offered by the state—whether explicitly or more commonly implicitly—in the case the bank experiences financial distress. Making such assessments not only calls for consideration of applicable laws and regulations, but also relevant institutional structures and policies, both historic and prospective. Moreover, the analysis must consider policies that, in an effort on the part of government to reduce *moral hazard*,[54] may be quite opaque. In sum, this aspect of the analytical process necessarily requires keen judgment, and is in consequence principally qualitative in character.[55]

[54] Industrial and service companies are thus far less likely to benefit from a government bailout, although this likelihood depends on the political–economic system. Even in highly capitalist countries, there are exceptions where the firm is very large, strategically important, or politically influential. The bailout of automaker Chrysler Corporation in the United States, a company that was later acquired by Daimler-Benz, was a notable illustration. More recently, the 2008 crisis prompted substantial government intervention in Europe and in the United States. In more *dirigiste* economies, state bailouts are less rare. Still, even in these economies, most corporates have no real lender of last resort, and must remain solvent and liquid on pain of fatal collapse. Perhaps, in consequence, their quantitative performance and solvency indicia tend to be scrutinized more severely than those of their financial institution counterparts.

[55] Aside from their relevance in such extreme circumstances, because of the degree to which bank performance is affected by government regulation and supervision, the same considerations are important in the ongoing analysis of a bank's financial condition.



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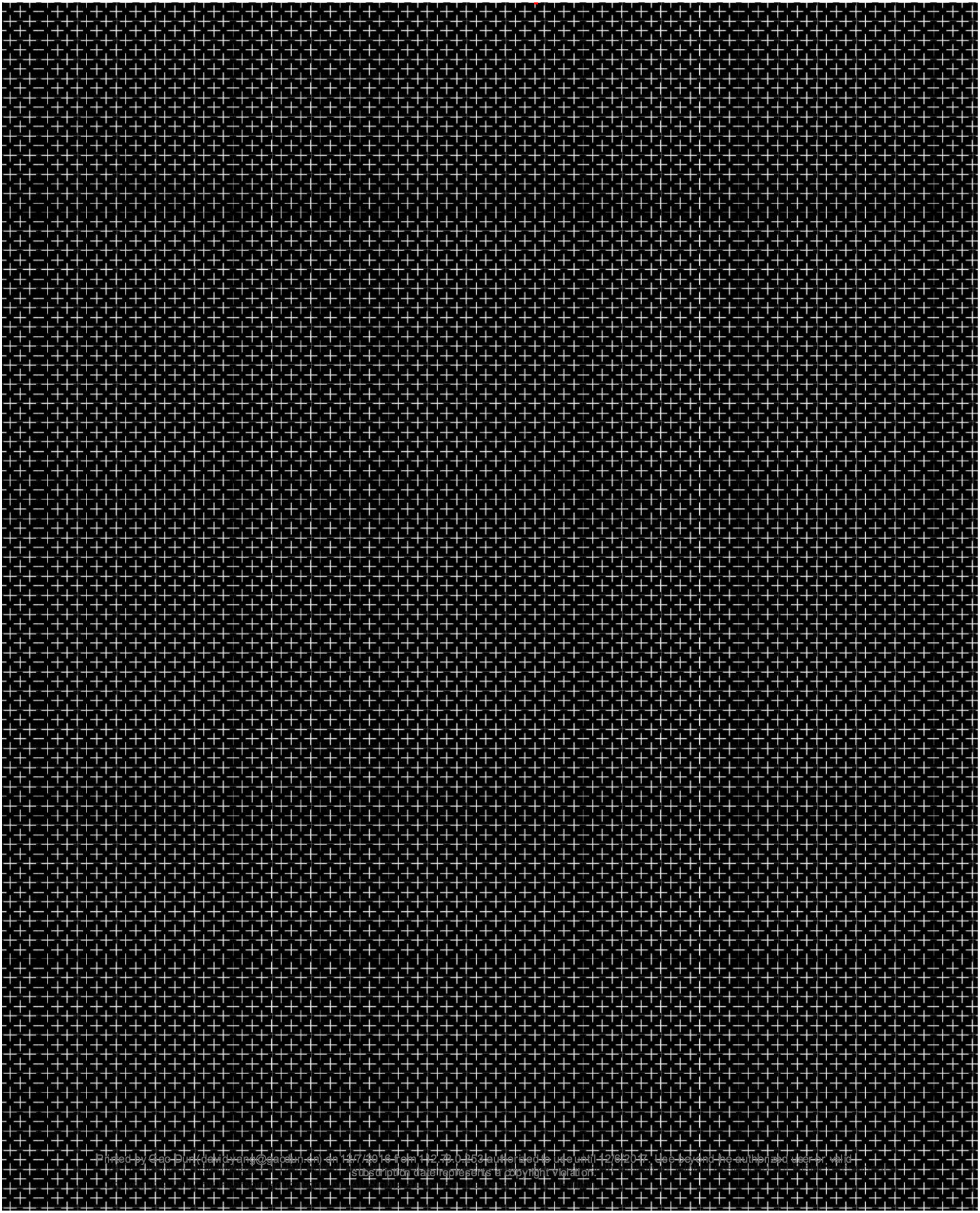

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# The Credit Analyst

# 2

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## Learning Objectives

After completing this reading you should be able to:

- Describe, compare, and contrast various credit analyst roles.
- Describe common tasks performed by a banking credit analyst.
- Describe the quantitative, qualitative, and research skills a banking credit analyst is expected to have.
- Assess the quality of various sources of information used by a credit analyst.

*Excerpt is Chapter 2 of* The Bank Credit Analysis Handbook, *by Jonathan Golin and Philippe Delhaise.*



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> Though the principles of the banking trade appear somewhat abstruse, the practice is capable of being reduced to strict rules. To depart upon any occasion from those rules, in consequence of some flattering speculation of extraordinary gain, is almost always extremely dangerous, and frequently fatal, to the banking company which attempts it.
>
> —Adam Smith, *Wealth of Nations*

> If you warn 100 men of possible forthcoming bad news, 80 will immediately dislike you. And if you are so unfortunate to be right, the other 20 will as well.
>
> —Anthony Gaubis[1]

What is a credit analyst?

What are the various types of credit analyst?

How do their roles differ?

Where do bank credit analysts fit in?

These are the questions this chapter seeks to answer.

Although all credit analysts undertake work that involves some similarity in its larger objectives, the specifics of each analytical role may vary a great deal. In the previous chapter, it was suggested that the approach to credit evaluation is contingent upon the type of entity being evaluated. In addition, the scope and nature of the evaluation will depend upon the functional role occupied by the analyst. Hence, while the same core questions underpin the analytical process, the time and resources available to perform the credit risk evaluation will vary.

This chapter seeks to survey the various subfields of credit analysis, as well as the different roles that can be undertaken within each corner of the field. The aim is to provide a practical overview of the field and to define the subject of our inquiry. To this end, credit analysis and credit analysts are classified in three different ways: by function, by the type of entity analyzed (as referenced above), and by the category of employer. Under this approach, some repetition is unavoidable. It is hoped, however, that by the end of the chapter the reader will have a good understanding of what credit analysis is, and where bank credit analysis fits into the larger picture.

[1] Anthony Gaubis (1902–1989) was an investment analyst and advisor who published a stock market newsletter, *Business and Investment Timing.* Obituary abstract, *New York Times*, October 11, 1989.

## THE UNIVERSE OF CREDIT ANALYSTS

Common sense tells us that the job of the credit analyst is to assess credit risk. Used without further modification, this encompasses a wide range of functions running the gamut from the evaluation of small business loan applications to rating corporate customers at a global bank. Consider, for example, the following four job descriptions below, each for a "credit analyst," drawn from actual advertised positions. While each listing is nominally for a credit analyst, the positions differ substantially in their content, scope of responsibility, and compensation.

### Job Description 1: Credit Analyst

Manage pipeline of loans. Review loans and customer documentation to ensure they meet requirements and to determine loan status (approve/decline), including data entry. Review property appraisals and relevant documentation and perform basic mortgage calculations to validate score-based approval. Refer loan applications over $750,000 to higher level.

### Consumer Credit

The first position deals with retail consumer credit, primarily mortgage lending. From the phrasing of the ad, we can see that the position is a relatively junior one with limited authority. The emphasis is less on detailed fundamental analysis and more on ensuring that documentation is in order, and that the loan applicant meets predetermined scoring criteria.

### Job Description 2: Credit Analyst

Review and analyze scoring analytics, interfacing as necessary with the risk management group. Develop, test, implement, and maintain a variety of origination and collection scorecards. Review modifications to existing systems. Prepare reports to support risk decisions.

### Credit Modeling

The second position also concerns consumer credit, but is not so involved with the analysis of individual exposures as the first. Instead of reviewing applications, this job involves the review and development of more refined



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consumer credit scoring systems. Both this and the first position are rather far afield from bank and financial institution credit analysis, which is the focus of this chapter.

## Job Description 3: Credit Analyst

Global investment bank seeks an experienced credit analyst to have responsibility for the analysis and credit rating of the bank's international corporate clients. The role will also include involvement in credit modeling and participation in credit committee presentations.

## Corporate Credit

The third advertisement is for a corporate credit analyst, since the scope of the position extends only to corporate entities, as opposed to financial institutions or sovereign credits. It also includes some duties with regard to the development of credit risk models.

## Job Description 4: Credit Analyst

Monitor exposures to counterparties, which comprise primarily banks, brokers, insurance companies, and hedge funds. Prepare counterparty credit reviews, approve credit limits, and develop and update credit policies and procedures. The credit review process includes detailed capital structure and financial statement analysis as well as qualitative assessments of both the counterparty and the sector in which it operates.

### THE COUNTERPARTY CREDIT ANALYST

Those credit analysts who evaluate the creditworthiness of financial intermediaries are known generally as bank and financial institution analysts. Within this broad category, the field can broadly be divided into two areas: (1) the analysis of banks and (2) the analysis of nonbank financial institutions (NBFIs) such as insurance firms or asset managers. When credit analysts are employed by a financial institution to analyze another financial institution, their evaluations are usually performed with a view to a prospective bilateral transaction between their employer and its opposite number as a counterparty. The credit risk arising from this type of transaction is termed *counterparty credit risk*, and those who evaluate such risk on behalf of prospective transaction participants are *counterparty credit analysts.*

As part of the evaluation process, *counterparty credit analysts* ordinarily assign the counterparty an internal rating. In contrast to the rating agency analyst who assigns an external rating, the counterparty credit analyst may be called upon to make recommendations concerning:

- Prudent limits in respect of particular credit risk exposures
- The approval or disapproval of a particular credit application
- Appropriate changes to the amount of exposure, tenor, collateral, and guarantees or to contractual provisions governing the transaction

## Counterparty Credit

Only the final listing specifically addresses the type of work that is the main subject of this chapter. It calls for a counterparty credit analyst to analyze banks and other financial institutions, while, like the third advertisement, it also embraces some supplementary responsibilities. From these job descriptions, which by no means take in all the main analytical roles, it is apparent that the field of credit analysis is wide and varied.

The majority of credit analysts are employed by financial intermediaries participating in the money and capital markets. Others work for nonfinancial corporations and for organizations that provide market-support functions, such as rating agencies and government regulators. While all credit analysts evaluate credit risk, the analytical role embraces a broad range of situations and activities—as the preceding descriptions make apparent. The credit officer at a small rural bank may have to decide whether a loan should be extended to a retail hardware store owner whose establishment the officer visits regularly. At the other end of the spectrum, the head of credit at a multinational bank may hold responsibility for setting country risk limits and for determining the credit lines to be extended to specific banks and corporations in that country, as well as having on-the-spot authority for approving or rejecting specific transactions.

The evaluations undertaken by credit analysts at rating agencies such as Moody's Investors Service, Standard & Poor's, and Fitch Ratings in assigning unbiased rating grades to debt issued by governments, corporations, financial institutions, and other entities, represent another corner of the field. *Sell-side* and *buy-side* fixed-income analysts, who work respectively for investment banks or banking divisions, or for hedge funds, and proprietary trading units, are concerned not only with credit risk but also with the relative value of debt instruments in



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comparison with issues in the same class and their corresponding desirability as investments. Finally, bank examiners and supervisors are also engaged largely in credit analysis as they evaluate the soundness of individual institutions as part of their supervisory function.

## Classification by Functional Objective

Within the universe of credit analysis, practitioners can also be differentiated in terms of their functional role. Most are employed primarily to evaluate credit risk as part of a larger risk management function performed by all manner of financial institutions, as well as by many nonfinancial companies. A smaller group are fixed-income analysts who are employed to help choose investments in debt securities or to find investment opportunities. This distinction between risk management and investment selection has a significant impact on the analyst's objectives and on his or her day-to-day work.

## Risk Management versus Investment Selection

The role of most credit analysts is to facilitate risk management, in the broadest sense of the term, whether at the level of the individual firm or at the level of national policy. The sort of risk management with which a credit analyst is concerned is, of course, credit risk management. Credit risk management forms part of the broader enterprise risk management function that includes the oversight and control of *market risk*, *liquidity risk*, and *operational risk.* Within the private sector, the main responsibility of credit analysts operating in a risk management capacity is to research prospective customers and counterparties, to prepare credit reports for internal use, to make recommendations concerning transactions and risk limits, and to generally facilitate the risk management of the organization as a whole.

Within the public sector, bank examiners are at heart credit analysts. They are employed by agencies that regulate financial institutions. As part of their supervisory function, they undertake independent reviews of specific institutions, typically from a credit perspective. The usual aim of these regulatory agencies is to maintain a sound financial system while seeking both to encourage investment and foster economic growth and to facilitate the creation of deep and liquid financial markets.

Rating agency analysts, although not directly involved in risk management, evaluate issuers, counterparties, and debt issues from a similar perspective. Their mission is to provide unbiased analysis as the basis upon which to assign ratings to issuers or counterparties, as well as to specific debt issues or classes of debt issues, when required. These ratings are, in turn, used to facilitate both risk management and investment selection. In addition to the rating agencies, a number of other sources exist, offering various degrees of independence, relevance, and analytical depth.

Those credit analysts involved in investment selection represent a smaller portion of the field. Most credit analysts that perform this function can be classified as fixed-income analysts. Investment selection, of course, refers to the identification of potential investments (or those to avoid), and the making of recommendations or business decisions concerning how to allocate funds available for investment, from which the investor expects to make a return over time. In the investment context, credit risk is of particular importance in respect to fixed-income securities and other debt instruments; hence, its assessment comprises the larger part of the fixed-income analyst's work. It is normally less of a concern in respect to equity securities since the inherent trade-off accepted by equity investors is that a significant upside potential implies greater credit risk. Nonetheless, equity analysts implicitly take account of credit concerns and do, from time to time, address those concerns explicitly in investment reports. For both the equity analyst and the fixed-income analyst, the main objective is to reach a conclusion as to whether a particular investment will generate the expected return and whether it is more apt to exceed expectations or fall short of them.

In analyzing a fixed-income security, the risk of default is always an underlying concern, if not the analyst's chief focus. In most instances, the analyst's principal concern is the potential deterioration in an investment's credit quality and the corresponding risk of a decline in its price. All other things being equal, increased credit risk will cause a given debt security's price to fall. In contrast to the counterparty credit analyst, the fixed-income analyst is concerned not only with the credit risk of a contemplated transaction, but also with the investment's *relative value.* In brief, relative value refers to relative desirability of a particular debt security vis-à-vis securities in the same asset class and having the same assigned rating and other fundamental characteristics. It represents a key input in the fixed-income analyst's recommendation concerning a security—for example, whether to buy, sell, or hold it as an investment.



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It should be noted that often within a financial institution, the functions of risk management and investment selection are largely separate domains. Their separation may be reinforced through the establishment of a so-called Chinese Wall constructed at the behest of regulators to limit the flow of certain types of information to prevent the unfair exploitation of inside information by customers or traders. Such barriers and the divergent objectives of credit analysts employed in a risk management capacity vis-à-vis those employed in an investment selection tend to discourage collaboration between the two types of staff.

## Primary Research versus Secondary Research

Although in respect to the evaluation of credit risk, the basic elements of each of the previously mentioned analytical roles are similar, the amount of time and resources available to an analyst to assess the relevant credit risk depends very much upon the nature of the position. Credit analysis, when undertaken by one or more individuals, requires time and resources. Accordingly, the cost of analysis is higher when it is performed with human input, as opposed to being processed using a credit scoring mechanism. The more primary research required, the higher the cost. Notwithstanding the benefits of conducting a comprehensive credit risk review, it may not be cost-effective to perform an in-depth assessment in all situations where credit risk arises. The cost factor explains why the "analysis" of small standardized transactions is frequently automated, by the use of a *credit risk model* incorporated into a computer software application. While this chapter does touch upon the automated modeling systems that underpin *credit scoring*, it is primarily concerned with *analyst-driven credit research.* Such research and the evaluation of credit risk based on that research takes into account both quantitative and qualitative criteria, and considers both microeconomic (bank-specific) variables as well as the macroenvironment, including political, macroeconomic, and industry/systemic factors. This type of evaluation process may also be termed *fundamental credit analysis.*[2]

The same cost rationale constrains counterparty credit analysts as well, albeit to a lesser extent. The analysis of banks and other financial institutions, for reasons to be discussed, is not wholly amenable to quantification and thus cannot be fully automated. Nevertheless, the time and resources to perform credit reviews is limited, given that a counterparty credit analyst employed by a financial institution may well be responsible for an entire continent or region—for example, Asia—and his or her brief may extend to a hundred or more banks. Obviously, such an individual will not be able to visit every bank within his or her purview, nor spend several days analyzing a single institution. Although, ideally, counterparty credit analysts will conduct an independent review of the bank's financial statements, and may, in some cases, periodically call or visit the subject bank, the greater part of the counterparty credit analyst's work will tend to be taken up by researching the ratings produced by third parties, taking into account recent developments and utilizing other available sources of information to arrive at a synthesis of the institution's credit story. Naturally, the conclusions reached will incorporate the analyst's own assessments. The form of the resulting credit report will vary from institution to institution. Since the analysis and the recommendations made are intended purely for internal purposes, the reports that contain them will be briefer than those produced by rating agencies and considerably briefer than those produced by sell-side analysts at investment banks. Ordinarily, the entire report will rarely exceed two or three pages, and will simply include a short executive summary followed by a page or two of supporting text.

The credit analyst employed by a rating agency is, as a rule, under much less severe limitations. One reason is that nowadays most ratings are *solicited*, meaning that they are paid for by the party being rated or issuing the instrument that is to be assigned a rating. Unlike in-house corporate and counterparty analysts who often rely upon the assessments made by the rating agencies, it is the rating agency analysts themselves who are expected to produce a comprehensive and in-depth credit evaluation. By undertaking the intensive primary research that forms the foundation of the rating assignment, rating agency analysts provide the value-added service to their subscribers that allows the latter to complete credit reviews in an expeditious manner. In addition to examining the bank's financials, rating agency analysts almost invariably visit the bank in question to form an independent conclusion as to its creditworthiness. Bank visits and accompanying

[2] Until now, we have looked at credit analysis in a general way. With this chapter, we begin to concentrate on the credit analysis of financial institutions generally and on banks specifically.

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due diligence investigations are fairly time-consuming, taking at least the better part of a day, and sometimes significantly longer. Additional time is needed to prepare the final report and have it approved by the agency's rating committee. To ensure that enough resources are allotted to produce a high-quality credit evaluation, each rating agency analyst typically covers a fairly small number of institutions, often in a small number of countries.[3]

## A Special Case: The Structured Finance Credit Analyst

Finally, another type of credit analyst whose province does not easily fit within the preceding categories and whose functions are generally outside the scope of this book must be mentioned: the structured finance credit analyst.[4] Structured finance refers to the advance of funds secured by certain defined assets or cash flows. The credit analysis of structured products is often complex because the resulting credit risk depends primarily on the manner in which such assets and cash flows are assembled, and in particular upon the forecasting of the probability of various contingencies that affect the ownership of such assets and the amount and timing of the associated cash flows to create a transaction framework.

Although, in principle, structured finance methods resemble ordinary secured lending backed by collateral, they are often considerably more complex, and the additional security is typically provided in a considerably more sophisticated manner, either by means of the transfer of assets to a special purpose vehicle (SPV) or synthetically, through, for example, the transfer of credit risk using credit derivatives. Instead of being based solely on the intrinsic creditworthiness of the issuer or borrower, structured products analysis takes account of a large variety of other criteria. Note that in the wake of the global credit crisis of 2007–2010, demand for structured products fell significantly. It can be expected, however, that at some stage demand may resume, albeit not to the same extent as previously nor for the breadth of complex instruments as existed before the crisis.

## By Type of Entity Analyzed

Credit analysis is usually categorized into four fields. These correspond to the four basic types of credit exposures, namely:

1. Consumer
2. Corporate
3. Financial institution
4. Sovereign/municipal (subnational)

As illustrated in the first two job descriptions provided at the beginning of this chapter, the consumer credit analyst only rarely engages in intensive examination of an individual's financial condition. Because, as suggested, case-by-case intensive analysis of individuals for personal lending purposes is seldom cost-effective, most consumer credit analysis is highly mechanized through the use of scoring models and similar techniques. As a result, unless concerned with modeling, systems development, or collateral appraisal, consumer credit roles often tend to be broadly clerical in nature. Hence, for our purposes, the main areas of credit analysis can be simplified to three as follows:

1. Corporate
2. Financial institution
3. Sovereign/municipal

Each of these fields—corporate credit analysis, sovereign credit analysis, and financial institution credit analysis—is a specialty in its own right. This chapter focuses on the analysis of financial institutions, and, more particularly, on the analysis of banks. Both corporate credit analysis and sovereign/municipal analysis are, however, discussed as a passing knowledge of each field is useful background for the bank credit analyst.

Note that, in practice, there is often a degree of overlap among the categories. Within a particular institution a single analyst may, for example, be responsible for both financial institutions and corporates. In a similar fashion, the analysis of sub-sovereign entities such as

[3] It is worth noting here that between the two extremes just discussed—the due diligence undertaken by rating agency analysts and the automated scoring of credit risk using a quantitative model—hybrid systems are employed in the counterparty credit context, encouraged also by the requirements of Basel II and Basel III. Under a hybrid approach, some rating inputs are generated using quantitative data supplied from internal sources or an outside provider, while more qualitative scorings are entered by the analyst. They represent an attempt to reduce costs and enhance the consistency of ratings, while seeking to incorporate analyst judgments where quantitative models are unwieldy.

[4] Although basic structured finance transactions such as mortgage-backed securities and similar securitizations are discussed briefly in some of the pages that follow, the analysis of such transactions remains wholly outside the scope of this chapter.

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municipalities or public sector agencies may be grouped as a separate category from sovereign analysis or combined with corporate or financial institution analysis.

Finally, in the realm of both counterparty credit analysis and fixed-income analysis, in respect to the three categories of credit analysis discussed below, a distinction can be made between (1) the generic credit evaluation of an issuer of debt securities, without reference to the securities issued; and (2) a credit evaluation of the securities themselves. As a rule, an analysis of the former is a prerequisite to conducting an analysis of the latter.

## Corporate Credit Analysts

Corporate credit analysts evaluate the credit risk of nonfinancial companies, such as industrial enterprises, trading firms, and service providers, generally for purposes of either lending to such organizations, holding their securities, or providing goods or services to them that give rise to credit risk. Since banks primarily lend not to other banks but to nonfinancial organizations, the preponderance of credit analysis performed within banks is corporate in nature. Compared to the analysis of financial institutions, where ongoing and long-standing counterparty relationships with other financial institutions involving multiple transactions are customary, corporate credit analysis tends not only to be more specialized by industry, but also more oriented toward specific transactions as opposed to the establishment of continuing relationships.

The largest of the three main areas in which analyst-driven research is performed, corporate credit analysis is also the most diverse, ranging considerably in terms of the industrial and service sectors, products, scale, and the geographical regions of the firms that are the targets of evaluation. While the core principles of corporate credit analysis remain largely the same across nonfinancial sectors, specific industry knowledge is often an important part of the corporate credit analyst's skill set. It follows that, while corporate credit analysis itself is an area of practice, within the field as a whole analysts frequently concentrate on particular industry sectors such as retailing, oil and gas, utilities, or media, applying sector-specific metrics to aid in their assessment of credit risk.

Such specialization within the realm of corporate credit risk evaluation is most apparent in fixed-income analysis and at the rating agencies, since both almost always involve more intensive and primary research than is required for risk management within financial institutions.[5] As an illustration, a U.S.-based global investment bank would approach the division of responsibility among corporate credit analysts with each analyst taking responsibility for just one or two sectors, while some analysts would have a regional brief. In this example, corporates are broadly classified as falling into one of the following sectors:

- Transportation and vehicle manufacture
- Paper and forest products
- Natural resources (excluding forest products)
- Chemicals
- Energy
- Property
- Telecom/media
- Utilities
- Sovereigns

In the same way that the sector being analyzed influences the analytical approach, so too may the scale of the business affect the analytical methodology. The analytical tools and metrics applied to small businesses—which are increasingly the target of bank business lending as large enterprises gain access to the capital markets—may differ from those applied to publicly listed multinational enterprises. Compared to large listed organizations about which there is much publicly available information, more field and primary research may be needed in respect to small- and medium-size enterprises as well as more intensive scrutiny of the owners and managers. Lastly, since cash flow analysis is especially critical in evaluating corporate credit risk and the analyst is likely to assess the creditworthiness of firms in more than one industry, accounting skills perhaps take on somewhat greater importance in the corporate credit realm than in respect to financial institutions.

## Bank and Financial Institution Analysts

Another category of credit analysis looks at banks and other financial institutions, and its corresponding objective is to assess the creditworthiness of financial intermediaries. In contrast to corporate credit analysis, this function will be only infrequently performed for the purpose of making conventional lending decisions. Instead, the analysis of a

[5] There are, of course, exceptions, as when a bank is contemplating advancing a very large loan or engaging in another type of transaction of comparable magnitude.

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particular bank is generally undertaken either in contemplation of entering into one or more usually multiple bilateral transactions with the bank as a counterparty. As noted previously, banks and other financial institutions can also be assessed with reference to and as part of an analysis of debt instruments or securities issued by such institutions.

### *Counterparty Credit*

As noted previously, the term *counterparty* refers to a financial institution's opposite number in a bilateral financial contract. The credit risk that arises from such transactions is often called *counterparty (credit) risk*, and bank and financial institution analysts whose role is to evaluate the credit risk associated with the transaction are frequently called *counterparty credit analysts.* Whatever their title, the focus of counterparty credit analysts is on the potential credit risks that result from financial transactions, including *settlement risk*.

Counterparty credit analysts may also have responsibility for setting exposure limits to individual institutions or countries, or participate in the process of making a decision as to whether to extend credit or not. Because the vast majority of financial transactions involve banks or other financial institutions on at least one side of the deal, counterparty credit analysts are generally employed mainly by such organizations. For the same reason, banks and other financial institutions are the principal targets of this type of credit analysis.

### *Product Knowledge*

To both counterparty and corporate credit analysts employed by a financial institution, the type of exposure anticipated, whether a conventional plain vanilla transaction or one more complex is contemplated, will often affect the analysis undertaken and the conclusions reached. The reason for this, which was discussed in the preceding chapter, is that the type of product from which the prospective credit risk arises can have a substantial impact on the severity of any loss incurred. Equally, the length of time over which the credit exposure will extend—that is, the tenor of the exposure—is an important credit consideration.

The vast majority of counterparty transactions involve the following product categories:

- Financing or obtaining funding directly through the interbank market on a senior unsecured basis
- Financing or obtaining funding through repurchase (repo)/reverse repurchase (reverse repo) transactions
- Financing or obtaining funding through the lending or borrowing of securities
- Factoring, forfeiting, and similar types of receivables finance
- Holding or trading of debt securities of banks and other financial companies for trading or investment purposes
- Foreign exchange (FX or forex) dealing, including the purchase or sale of FX options and forwards
- Arranging or participating in other derivative transactions including, for instance, interest rate swaps, foreign-exchange swaps, and credit derivatives
- Holding or participating in securitizations or structured finance that gives rise to counterparty credit risk
- Correspondent banking services, including trade finance effected through documentary letters of credit
- Custodial and settlement services

## Sovereign/Municipal Credit Analysts

A third category of credit analysis concerns the assessment of sovereign and country risk. Governments throughout the world borrow funds through the issue of fixed-income securities in local and international markets. Sovereign risk analysts are therefore employed to assess the risk of default on such obligations. (Technically, governments do not go bankrupt, although they may default on their obligations.) Sovereign analysis is, however, relevant not just to profiling the risk associated with government debt issues. It also provides the context for evaluating credit risk in respect to other exposures. Hence, sovereign analysts appraise the broader risks arising from cross-border transactions as well as from transactions directly with a nation, its subnational units (e.g., provinces and cities), or governmental agencies.[6]

Sovereign analysts make use of tools that are analogous to those utilized by analysts assessing the risk of corporate entities, but that take into account the peculiar

[6] A distinction is sometimes made between sovereign risk analysis and country risk analysis. The term *country analysis* tends to connote a greater emphasis on the impact of a nation's political, legal, and economic regime, together with potential changes in that regime, upon debt issuers within its borders, as well as those affecting the risks of foreign direct investment in the country. The difference between country risk and sovereign risk has become largely semantic, however, and in practice the terms are often used interchangeably.



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characteristics of governments. Instead of looking at company financials, sovereign analysts examine, among other metrics, macroeconomic indicators to gauge whether a government will have the wherewithal to repay its financial obligations to local and international creditors. Most sovereign risk analysts therefore have a strong background in economics. Sovereign risk also takes account of political risk, so it is also necessary for the analyst to have an understanding of the political dynamics of the country that is under review.

## The Relationship between Sovereign Risk and Bank Credit Risk

Sovereign risk and bank credit risk are closely linked, and each affects the other. In brief, the strength of a nation's financial system affects its sovereign risk and vice versa. For this reason, the level of country or sovereign risk associated with a particular market is a significant input in the credit analysis of banks located in that market. Although sovereign risk analysis is a distinct field from bank credit analysis, the bank credit analyst should have at least a passing familiarity with sovereign risk analysis (and vice versa). As part of the process of forming a view about the impact of the local operating environment on a particular banking industry, many bank analysts engage in a modicum of sovereign risk analysis while also relying upon the sovereign risk ratings and accompanying analyses published by the rating agencies or from internal divisions responsible for in-house assessments of sovereign risk.

Sovereign risk has two distinct but related aspects.

1. One is the evaluation of a sovereign entity as a debt issuer as well as the evaluation of specific securities issued by a sovereign nation, or by subnational entities within that nation.
2. The other is the evaluation of the operating environment within a country insofar as it affects the banking system.

Although the process of evaluating each aspect of sovereign, or country, risk is similar in both situations, they represent two discrete facets of credit risk analysis. The analysis of sovereign debt issues may seem to be outside the scope of this book, but, to the extent that such instruments are now found in the books of a growing number of banks, and even of small domestic banks, this will be of further concern to us. In contrast, the analysis of sovereign risk itself, as part of an evaluation of a bank's operating environment, is of critical importance to the overall evaluation of the institution's credit risk profile.

While sovereign risk is in itself relevant to the analytical process, bank credit analysts are particularly interested in the systemic risk associated with a given banking industry. Systemic risk, which is closely related to sovereign risk and arguably a subset of it, refers to the degree to which a banking system is vulnerable to collapse, and conversely, to the strength and stability (or conversely the fragility) of the banking sector as a whole. Systemic risk is largely synonymous with the risk of a banking crisis, a phenomenon characterized in part by the roughly contemporaneous collapse or rescue prior to collapse of multiple banks within a single jurisdiction. Figure 2-1 depicts the universe of credit analysis in a graphic format.

## Classification by Employer

Another way to understand the work that credit analysts perform is to look at the types of organizations that employ them. A bank credit analyst, for instance, generally

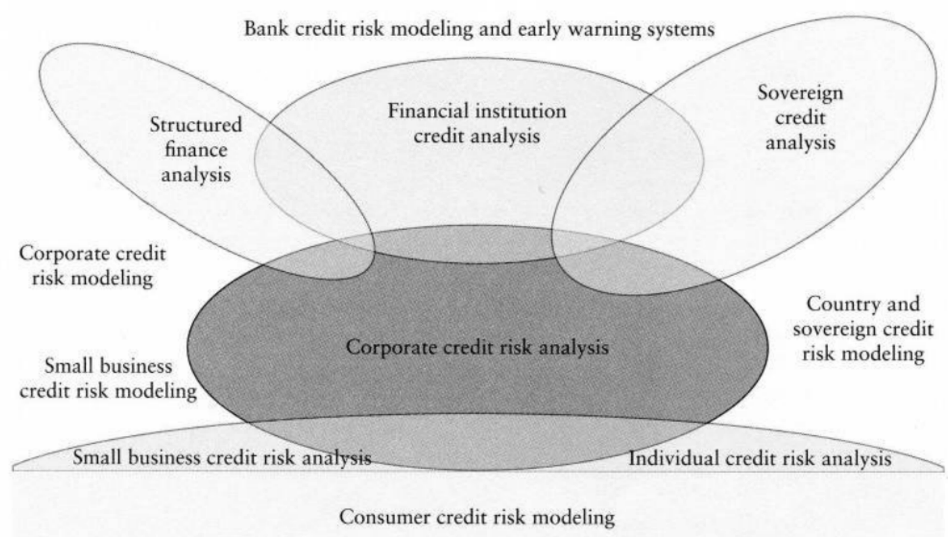


**FIGURE 2-1** The universe of credit analysis by subject of evaluation.

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works in one of four primary types of organizations, which closely correspond to the functional roles described above. They are:

1. Banks and related financial institutions
2. Institutional investors, including pension funds and insurance firms
3. Rating agencies
4. Government agencies

The first two categories are not entirely discrete. As discussed in the box labeled "Buy-Side/Sell-Side," banks and other financial institutions such as insurance companies may simultaneously function as issuers, lenders, and institutional investors, while other organizations that have investment as their primary function may offer additional services more typically associated with banks and may also include a significant risk management group.

> **BUY-SIDE/SELL-SIDE**
>
> Institutional investors, and the investment analysts employed by them, are collectively referred to as the *buy-side.* Intermediaries that attempt to sell or make markets in various securities, together with the analysts who work for them, constitute the *sell-side.* There is some overlap, and it is possible for a financial institution to be on the buy-side and the sell-side at the same time.
>
> For example, a bank may sell securities to customers while also trading or investing on a proprietary basis. Similarly, while insurance firms are nominally in the business of risk management, they are also major institutional investors. The premiums they collect need to be invested on a medium- or long-term basis to fund anticipated payouts to policyholders, and, as a result, they are important institutional investors. As with banks, credit analysts employed by investment management organizations generally work in either a risk management capacity or an investment selection capacity.

## Banks, NBFIs, and Institutional Investors

Banks constitute the largest single category of financial institutions, and are the largest employer of credit analysts. Aside from banks, nonbank financial institutions (NBFIs) are also significant users of these skill sets as well as being themselves objects of analysis. A major subcategory of NBFIs is comprised of investment management organizations. As discrete organizations, mutual funds, unit trusts, and hedge funds fall within this grouping.

## Rating Agencies

Rating agency analysts are credit analysts who work for rating agencies to evaluate the creditworthiness of banks, corporations, and governments. The three major global agencies are Moody's Investor Services, Standard & Poor's Rating Services, and Fitch Ratings. In addition, local rating agencies in various countries, sometimes affiliated with the big three, may play an important role in connection with domestic debt markets.

The three-step purpose of a rating agency analyst performing a credit evaluation for the first time will be to:

1. Undertake an overall assessment of the credit risk associated with the issuer
2. Evaluate the features of any securities being issued in respect to their impact on credit risk
3. Make a recommendation concerning an appropriate credit rating to be assigned to each

> **THE RATING AGENCY ANALYST**
>
> Credit analysts are employed by rating agencies to perform risk assessments that are distilled into ratings represented by rating symbols. Each symbol, through its letter or number designation, is intended to classify the rated institution as a strong, average, or weak credit risk, and various gradations in between. The assignment of a rating to the bank will typically be supported by an analytical profile, which represents the fruit of considerable primary research on the part of the analytical team.

The credit rating will be used by risk managers and investors to determine whether the exposure or investment is attractive, as well as at what price it might be worth accepting.

## Government Agencies

Governments function both as policy makers and regulators on the one hand, and as market participants on the other, issuing debt or investing through government-owned organizations. Government bank and insurance examiners are essentially credit analysts who function in a regulatory capacity, assessing the riskiness of a bank or



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THE RATING ADVISOR

One role that makes use of credit analytical skills but does not easily fit into the classifications in this chapter is that of the rating advisor. Usually a former rating agency analyst, the rating advisor is normally employed by investment banks to provide guidance to prospective new issuers in the debt markets. As a rule, the rating advisor will make an independent analysis of a prospective issuer to gauge the rating likely to be assigned by one or more of the major agencies, and then counsel the enterprise on how to address its likely concerns. The rating advisor's guidance will include advice on how to make a presentation to the rating agency analysts and how to respond to their questions. His or her job is as a behind-the-scenes advocate, seeking to obtain the best rating possible for the prospective issuer and working to see that it is given the benefit of the doubt when there is uncertainty as to whether a higher rating is justified over a lower one.

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insurance company to determine the institution's soundness and its eligibility to continue to do business. With regard to governments or their agencies that act as market participants, the scope and legal status of such wholly or partly state-owned entities vary considerably from country to country. Generally, credit analysts within these institutions function in a similar manner to their counterparts at privately owned enterprises.

### Organization of the Credit Risk Function within Banks

In looking more closely at those credit analysts who perform a risk management function on behalf of market participants, it may be useful to examine some common approaches to the organization of this function within institutions. There are several typical approaches. The usual one is to divide the functions between corporate, financial institution (FI), and sovereign credit risk. The specific topic of structured credit analysis might also constitute a separate team within the FI group.

## ROLE OF THE BANK CREDIT ANALYST: SCOPE AND RESPONSIBILITIES

Having surveyed the various types of credit analysts, we now examine the principal roles of the bank credit analyst in more detail. In the previous section, we saw that within the category of bank credit analyst are a number of different subtypes. In this section, our focus is on the counterparty credit analyst and the fixed-income analyst.

### The Counterparty Credit Analyst

The counterparty credit analyst is concerned with evaluating banks and other financial intermediaries as part of his or her own organization's larger risk management function. The need for the evaluation of credit risk exposure to banks is an especially important one.

### The Rationale for Counterparty Credit Analysis

Undertaking credit risk exposure to other financial institutions is integral to banking. Banks take on credit risk exposure in respect to other banks in a number of different circumstances including trade finance and foreign exchange transactions. With regard to trade finance, banks ordinarily seek to cultivate correspondent banking relationships globally in order to build up their capacity to offer their importing and exporting customers trade finance services. Depending upon the structure of the banking system within a particular country, the proportion of banks that are internationally active may represent a small or large percentage of the significant commercial banks.

Such banks will have correspondent banking relationships with hundreds of financial institutions worldwide, and in large countries, local and provincial banks will have similar relationships with their counterparts in other geographic regions. Hence, unlike a bank's corporate borrowers, which in most cases are likely to be based in the same region as the bank's head offices (unless the bank has significant overseas operations), its exposure to other financial institutions in the form of exposure to correspondent banks may extend halfway around the world.

In addition to the need of many banks to have international relationships with other banks around the world, under normal market conditions, banks frequently lend to and borrow from other banks. Such interbank lending serves to maintain a market for liquid and loanable funds among participating banks to meet their liquidity needs. Overall, exposure to other banks and other financial institutions is likely to be a substantial proportion of the bank's overall credit risk (although not so large in net terms as it is in nominal or notional terms). Despite the need for banks to maintain ongoing transactional relationships with other financial institutions, their characteristic high leverage, among other traits, makes them not



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insignificant credit risks. Elevated leverage on both sides of a transaction makes each counterparty extremely sensitive to risk, and protecting against such risk constitutes a significant cost of doing business.

Exacerbating the vulnerability of banks to credit risk with respect to other banks is the potential for a collapse of a single, comparatively small bank to have repercussions far out of proportion to its size. The adverse effects can affect the business climate and economy of a whole nation or region, while the failure of a major bank or multiple banks can be catastrophic, potentially resulting in a collapse of the local banking system. Although the total collapse of an internationally active bank is fairly rare in normal times, the events of 2008–2012 show how real a possibility they are.

## Credit Analyst versus Credit Officer

Like the fixed-income analyst, the counterparty credit analyst's research efforts are undertaken with the objective of reaching conclusions and recommendations that will influence business decisions. In the case of a counterparty credit risk evaluation, this often takes the form, as previously suggested, of a recommendation that a particular internal rating be assigned to the institution just analyzed. The context for such a recommendation may be an annual review or a specific proposal for business dealings with the subject institution (through the establishment of country limits or credit lines).

The scope of analytical responsibility varies from bank to bank. At some institutions, the roles are entirely separate. The credit analyst's responsibility may be limited to analyzing a set of counterparties, as well as particular transactions, and preparing analytical reports, but might not extend to making credit decisions, or undertaking the related work of recommending credit limits and making presentations to the credit committee. Instead, this function might be the sole responsibility of the credit officer. Normally, under such a structure, the credit officer has first gained experience as a credit analyst and has acquired the intensive product knowledge enabling him or her to rapidly gauge the risk associated with a specific transaction.

At other banks, these roles may be more closely integrated. The credit officer may also perform relevant credit analyses or reviews, and prepare applications for new credit limits or for annual reviews of existing limits. Irrespective of how the functions are defined at particular organizations, the term *credit officer* implies a greater degree of executive authority than that associated with the term *analyst*, which tends to connote an advisory rather than an executive function. Within financial institution teams, there may be a further functional separation between the role of the analyst and the role of the credit officer.

At the executive level, the principal objectives of the counterparty credit risk team are:

- To implement the institution's credit risk management policy with respect to financial counterparties by subjecting them to a periodic internal credit review, and with the aim of establishing prudent credit limits with respect to each counterparty.
- To evaluate applications for proposed transactions, recommending approval, disapproval, or modification of such applications, and seeing the process through to its final disposition.

As a practical matter, the relevant decision-making responsibility customarily extends to:

- *Authorizing the allocation of credit limits* within a financial institution's group or among various product lines.
- *The approval of credit risk mitigants* including guarantees, collateral, and relevant contractual provisions, such as break clauses.
- *The approval of excesses over permitted credit limits*, or the making of exceptions to customary credit policy.
- *Coordination with the bank's legal department* concerning documentation of transactions in order to optimize protection for the bank within market conventions.

Depending on the organizational structure, credit officers may liaise with other departments within the bank such as those that are charged with monitoring limit violations, margin collateral, and market risk. In addition, credit officers may have responsibility for reviewing and recommending changes in bank credit policies.[7]

The advent of Basel II and Basel III has meant that credit analysts must provide their skill also to a new, gigantic, range of tasks for the benefit of risk management departments. This has introduced a new set of parameters in how the credit analyst approaches his or her duties.

[7] Note that in regard to credit officers covering financial institutions, some banks make a distinction between trading-floor credit officers, who have responsibility for credit decisions involving investment and trading operations, and those responsible for approving simple trade finance transactions, correspondent banking, and routine cash management activity, such as interbank borrowing and lending.



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**TABLE 2-1** Selected Financial Products

| Simple Financial Products | More Complex Financial Products |
|---|---|
| Term loans | Mortgage-backed securities |
| Documentary letters of credit | Asset-backed securities |
| Money market investments/obligations | Credit default swaps |
| Investments in bonds/bond issues | Structured investment facilities |
| Spot transactions | Structured liquidity facilities |
| Interest rate swaps | Weather derivatives |

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## Product Knowledge

Credit analysis cannot be divorced from its purpose or context. Certainly, the overall and ultimate objective of the credit risk management framework within which counterparty credit analysis takes place is to optimize—within regulatory constraints and internal parameters—return on risk-adjusted capital. The myriad of financial products that a bank offers to its customers, however, together with the various trading and investment positions it takes in the operation of its business, engender a multitude of specific credit exposures. The more common of these were enumerated in the preceding section concerning bank and financial institution analysts. A more systematic list is provided in Table 2-1.[8]

Although counterparties are likely to first be graded without regard to a particular transaction, a full estimation of credit risk requires that specific transactions also be rated with reference to the type of obligation incurred.[9] In comparison to the expansive categories of obligations evaluated by rating agencies, a bank goes beyond a "rating exercise" to make decisions concerning specific limits on exposure and the approval or disapproval of proposed transactions, together with required modifications if not approved in full. Such decisions cannot prudently be made without product knowledge,[10] which refers to the in-depth understanding of the characteristics of a broad range of financial products. These characteristics include:

- The impact of the proposed transaction on the borrower's financials
- The features of the obligation or product and its risk attributes
- The amount and type of credit risk mitigation
- Any covenant agreed to by the borrower

There, credit analysis of the counterparty as a discrete entity merely represents only one input in the decision-making process. An equally essential part of the analytical process is the understanding of the risks associated with particular products or transactions. The counterparty credit analyst provides the initial credit evaluation supporting a recommendation concerning decisions on these points. Depending upon how responsibilities are divided, it may be up to the credit analyst or the credit officer to supply the product knowledge against which appropriate credit judgments can be made. These decisions—as to whether an individual transaction will be entered into, and under what terms—are, of course, made with reference to internal policies and procedures.

[8] Although for illustrative purposes we have frequently used the example of simple loan transactions, the credit exposures to which a bank may be subject are extremely diverse. They run the gamut from such basic term loans to highly sophisticated derivatives transactions and structured finance transactions. Each has its own risk characteristics, and risk-conscious financial institutions will ordinarily have credit policies in place governing their exposure to various types of transactions.

[9] Similarly, external rating agencies will ordinarily evaluate a counterparty in a general manner, while debt securities will be assigned ratings based on features of the sort just mentioned. Issuer ratings may be made with reference to a specific debt issue or to a class of generic issues. Whether the issue rating is affected by the issuer rating assigned will depend upon the characteristics of the issue. In the recent past, the ratings of many structured products were decoupled from the ratings of the issuer or originator.

[10] It is not unusual for considerations beyond the estimated credit risk to affect the decision as to whether to approve or reject an application for a loan or other service or product subjecting the bank to credit risk. Such considerations could include the bank's historical or desired future relationship with the customer, including the prospect of other business and similar considerations.



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## AN ADVERSARIAL ROLE?

Whether supporting proprietary trading operations or customer business, the relationship between the credit officer and the front office is rarely adversarial. While the credit officer usually has the right to reject a proposed transaction, he or she must generally remain cognizant of the fact that banking is a risk-taking business and that it is profits from such risk taking that pay the bills.

Consequently, the credit officer is generally expected to be receptive to concerns of the business and to look for ways to meet changing business needs while protecting the bank against undue credit risk exposure. The most successful banks are those that welcome and manage risk, and that price and hedge that risk appropriately, and the most effective credit officers are those who understand that a balance must be maintained between profits and prudence.

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## The Fixed-Income Analyst

Credit analysts, as we have seen, may function not only as risk analysts, assessing and managing risk, but also as investment analysts assisting in the selection of investments. A relatively small proportion of these fixed-income analysts cover financial institutions. Such analysts may specialize in banks, or banks may just comprise a portion of their portfolio. Like equity analysts, fixed-income analysts make recommendations on whether to buy, sell, or hold a fixed-income security such as a bond. That is, they must ascertain the relative value of the security. Is it undervalued and, therefore, a good buy, or overvalued and consequently best to sell?

## Approaches to Fixed-Income Analysis

Fixed-income analysis can be divided into fundamental analysis and technical analysis. Fundamental analysis explores many of the same issues that are undertaken when engaging in credit analysis for risk management purposes; that is, default risk. But the definition of credit risk applied may differ to a degree from that utilized by the counterparty credit analyst or the corporate credit analyst. Technical analysis looks at market timing issues, which are affected by the risk appetite of institutional investors and market perception, as well as pricing patterns. Investor appetite is often strongly influenced by headline events, such as political crises, foreign exchange rates, and rating actions, such as upgrades or downgrades, by credit rating agencies. Most fixed-income analysts consider both fundamental and technical factors in making an investment recommendation.

## THE FIXED-INCOME ANALYST

The fixed-income analyst's goal is to help his or her institution make money by making appropriate recommendations to traders and to clients. As part of this objective, the fixed-income analyst seeks to determine the value of any debt securities issued by the bank, taking account of market perceptions, pricing, and the issue's present and prospective creditworthiness. This analysis is used to make recommendations to traders or investors to help them decide whether to buy, sell, or hold a given security.

## Impact of the Rating Agencies

The impact of rating agencies on fixed-income analysis is twofold.

First, by providing independent credit assessments of bond issues and of sovereign risk, rating agencies facilitate the establishment of benchmark yield curves, and thereby strengthen markets and enhance liquidity. At the same time, assigned ratings tend to foster a market consensus on a particular issuer and thereby provide a basis for the determination of the relative value of the issuer's securities.[11]

Second, the perception of the likelihood of a rating action, both as an indicator of fundamentals and irrespective of them, may be factored into an investor's calculus. Ratings therefore play a critical role in fixed-income analysis in regard not only to the fundamentals they reveal, but also the probability of rating actions being taken and the timing of such actions. See box entitled "Rating Migration Risk" in the previous chapter, page 19.

[11] Fixed-income analysts tend to integrate fundamental and technical analysis to a greater degree than do equity analysts. (Equity analysis is discussed in the following subsection.) Both equity and fixed-income analysis vary in respect of the audience to which the analytical reports are targeted. In the case of investment banks and brokerages, fixed-income analysis may be intended for clients, often institutional investors or asset managers, who will use the research to make their own trading decisions. Alternatively, fixed-income analysis may be intended primarily for a firm's own traders, who will use the research internally.



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Whether designed for a bank's customers or the bank itself, fixed-income analysis requires a good understanding of:

- The elements that affect creditworthiness
- How the issue and the issuer are perceived by the market
- Market movements and dynamics
- How rating agencies operate

Often fixed-income analysts have had prior experience working as rating agency analysts.

## A Final Note: Credit Analysis versus Equity Analysis

Much of the published analysis available on banks is produced by equity analysts for stock investors rather than by credit analysts. The reason is that bank stocks are often of greater interest to the larger investment community than bank debt securities, which, at least in the past, were not as widespread globally as equity securities.

The focus of equity analysis, it must be acknowledged, is often antithetical to the aims of credit research. Equity analysis concentrates on determining whether a prospective investor should invest in the shares of a particular firm. The core questions that equity analysis seeks to answer are:

- Which course of action will best profit an investor: to buy, sell, or hold the securities of the subject company?
- What is the appropriate value of the company's securities, based on the best possible assessment of its present and future earnings?

Bank equity analysts, therefore, almost exclusively confine their analysis to publicly listed financial institutions (i.e., banks listed on a stock exchange), although they might also analyze a bank that is about to list or a government-owned bank that is about to be privatized.

A principal indicator with which equity analysts are concerned in determining an appropriate valuation is return on shareholders' equity (ROE), a number that reflects the equity investor's return on investment. Since ROE is closely correlated with leverage, higher profitability does not necessarily imply higher credit quality; instead, as common sense would dictate, risk often correlates positively with return. In contrast to the equity analyst, the credit analyst tends to give greater weight to a variety of financial ratios that reflect a bank's asset quality, capital strength, and liquidity. Together, such indicators reflect the institution's overall soundness and ability to ride out harsh business conditions rather than merely its ability to generate short-term profits.

Another salient difference between credit analysis and equity analysis concerns the extent to which financial projections are utilized. Equity analysts normally base their share price valuations on financial projections. (Such projections are, of course, derived from the historical data.) In contrast, historical financial data is the principal, if not sole, focus of credit analysts.[12]

Despite this critical difference in approach between the equity analyst and the credit analyst, neither equity nor credit analysts are necessarily oblivious to credit or valuation concerns. Since shareholders are theoretically in the first loss position should a bank fail, it is understandable, and indeed crucial, that equity analysts pay some attention to credit risk. Indeed, credit considerations come to the fore during times of economic stress. The Asian crisis of 1997–1998 highlighted the need for analysts in the region to take into account a company's financial strength and external support, as well as its profitability. Following the crisis, as Lehman Brothers' analyst Robert Zielinski noted:

> In the past, most of the focus of an analyst's research was on the earnings line of the income statement. The analyst projected sales based on industry growth, profit margins, and net income. The objective was to come up with a reasonable figure for EPS growth, which was the main determinant of stock valuation. . . . Today, the analyst places most of his emphasis on the balance sheet. Indeed the most sought-after equity analysts in the job market are those who have experience working for credit rating agencies such as Moody's.[13]

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[12] This was not because credit risk analysis was not forward-looking, but because traditionally financial projections were perceived as too unreliable. While accuracy in financial projection remains notoriously difficult to achieve, it would not be surprising if the use of financial projections to a limited degree, for the purpose of identifying potential unfolding scenarios, for example, could become more commonplace in the credit review context.

[13] Robert Zielinski, Lehman Brothers, "New Research Techniques for the New Asia," December 14, 1998.



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## ARE EQUITY INVESTORS SUBJECT TO CREDIT RISK?

In discussing the influence of credit analysis on equity analysis and vice versa, an interesting question arises as to whether equity investors are exposed to credit risk. Are they?

Although the purchase of ordinary shares will often be subject to settlement risk, a form of credit risk, if that risk is put aside, then the answer, formally speaking, is "no." Credit risk presumes the existence of a definite financial obligation between the creditor and the party to whom the credit is exposed to the risk of loss through the possibility of default. In other words, for credit risk to exist, there must be a corresponding financial obligation, either present or prospective, between the issuer and the investor.

A common shareholder of an equity security is subject to a risk of loss but as a rule there is no financial obligation to redeem the investor's shares. His or her investment is perpetual, and no firm claim exists upon the firm's assets; the claim is only upon the excess of assets over obligations to creditors at the time of liquidation. Similarly, there is no right on the part of the ordinary shareholder to dividends. Hence an equity shareholder is not subject to credit risk, though he or she is subject to market risk—the risk that the value of the investor's shares will drop to zero.

In view of the weak position of shareholders vis-à-vis creditors in the event of a bank's failure, an equity investor is likely to be sensitive to the possibility of the value of his or her investment being wiped out completely. Insofar as the prospect of not just a zero percentage return but the loss of the entire investment is linked to the credit profile of the bank, which it indeed is, equity investors in practice are likely to perceive credit risk even if as shareholders they have no formal right to redeem their investment and must wait in line behind creditors in the event of liquidation. In any event, whether or not credit risk formally exists in relation to equity investors, there is no reason to think that credit assessment techniques should not be of benefit to equity investors in certain instances. In the same way that a fall in the credit quality of a debt security generally results in a lower market price for the debt security, a decline in the credit quality of an enterprise that issues both debt and equity will tend to register downward pressure on the prices of both its debt and equity securities—all other things, of course, remaining equal. Hence, it would be entirely appropriate for equity analysts to employ the techniques of credit analysis to evaluate their prospects in such situations.

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In a similar vein, a banking institution with a high proportion of bad loans and correspondingly high credit costs will probably not be the first choice for an equity analyst's buy list.

Likewise, equity market conditions and performance of a particular bank stock may, on occasion, be of interest to the bank credit analyst. For instance, dramatic falls in a bank's stock price as well as the existence of long-term adverse trends are worth noting as they may, but not necessarily, suggest potential credit-related problems. Similarly, the credit analyst should have some sense of the bank's reputation in the equity markets as that may have some effect on the institution's capacity to raise new capital if required.[14] This, in turn, will influence the perceived capital strength and liquidity of the institution.

## CREDIT ANALYSIS: TOOLS AND METHODS

As with any field, credit analysis utilizes various tools and resources, employs recognized methods and approaches, and generates customary types of work products. In the usual course of events, the analyst will:

- *Gather information* concerning a subject entity and industry from a range of sources.
- Distill the data into a *consistent format.*
- *Compare* the financial and other data with similar entities (peers), and to past performance.
- *Reach conclusions* (and possibly make recommendations) that are ordinarily expressed in writing as credit reports or credit profiles.

Although credit analysis in its various permutations has the same paramount goal—to come to a determination as to the magnitude of risk engendered by a credit exposure,

[14] Likewise, the bank's share price and recent or long-term price trends or volatility may very well have an impact on its ability to raise capital, or access liquid funds. For this reason, some credit analysts keep a weather eye on a bank's share price as a proxy for impending difficulties that may manifest in credit problems. More broadly, the usefulness of equity research, its techniques, or the fundamental data upon which it is based, depends on the bank analyst's role, the comparative availability of data for the institution that is the subject of analysis, and, naturally, upon whether the analyst has access to such material.



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## APPROACHES TO EQUITY ANALYSIS

Equity analysis can be divided into two broad approaches: fundamental analysis and technical analysis. Fundamental analysis examines the factors affecting a company's earnings, including the company's strategy, comparative advantages, financial structure, and market and competitive conditions. It attempts to ascertain whether the firm's shares are undervalued or overvalued with respect to the firm's present and projected future earnings. Thus, the core of the equity analyst's work revolves around the constructing of financial projections upon which the analyst's estimated valuations are based. Making projections is largely about making assumptions. Assumptions inevitably embody an element of subjectivity, and small differences in assumptions can result in large differences in the resulting calculations of expected future stock prices. Regardless of how estimated future prices are calculated, the resulting figures will determine in large part whether a recommendation to buy, sell, or hold is made.

Technical analysis looks at patterns or, more accurately, perceived patterns, in share price movements to attempt to predict future movements. To the technical analyst, these patterns express common archetypes of market psychology, and technical analysis emphasizes the timing of the decision to buy or sell. Most equity analysts, whether covering banks or other companies, employ fundamental rather than technical analysis as their primary tool, although technical factors will often be given some consideration. As opposed to technical analysis, fundamental analysis is relatively unconcerned with market timing issues. Instead, it presupposes a generally efficient market amid which temporary inefficiencies may arise, enabling investors to find bargains. A corollary belief is that the market will ultimately recognize the true value of such bargains, causing share prices to rise to a level that better corresponds to that true value.

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or conversely the creditworthiness of an entity—the analytical approach used will differ according to the circumstances.[15] Hence, the combination of tools, methods, and the resulting work product will differ according to the nature of the analyst's role.

## Qualitative and Quantitative Aspects

Credit analysis, as suggested in Chapter 1, is both a *qualitative* and a *quantitative* endeavor, involving a review of the company's past performance, its present condition, and its future prospects. Aside from the purely mechanical credit scoring exercise, it is practically impossible to undertake an entirely objective credit analysis that considers only quantitative criteria. Similarly, a solely qualitative evaluation performed without quantitative indicia to support it is arguably more vulnerable to inconsistency, human prejudice, and errors of judgment. In practice, the two aspects of analysis are inextricably linked.

## Quantitative Elements

The *quantitative* element of the credit assessment process involves the comparison of financial indicators and ratios—for example, percentage rates of net profit growth or, in the case of a bank, its risk-weighted capital adequacy ratios. The juxtaposition of such indicators allows the analyst to compare a company's performance and financial condition over time, and with similar companies in its industry.[16] In short, the quantitative aspect of credit analysis is underpinned by *ratio analysis.*

## Qualitative Elements

Not all aspects of a company's financial performance and condition can be reduced to numbers. The *qualitative* element of credit analysis concerns those attributes that affect the probability of default, but which cannot be directly reduced to numbers. Consequently, the evaluation of such attributes must be primarily a matter of judgment. For example, the competence of management is relevant to a firm's future performance. It is management, of course, that determines a firm's performance targets, plans how to reach these objectives while effectively managing the company's risks, and that is ultimately responsible for a company's success or failure. Ignoring such qualitative criteria handicaps the analyst in arriving at the most accurate estimation of credit risk. Certainly,

[15] Recall that in Chapter 1, we observed that the category of borrower would influence the method of evaluating the associated credit risk.

[16] In most cases, credit analysis relies on historical financial data. In some situations, however, quantitative projections of future financial performance may be made.



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## RATIO ANALYSIS

Ratio analysis refers to the use of financial ratios, such as return on equity, to measure various aspects of an enterprise's financial attributes for the purpose of respectively identifying rankings relative to other entities of a similar character and discerning trends in the subject institution's financial performance or condition. Ratios are simply fractions or multiples in which the numerator and denominator each represent some relevant attribute of the firm or its performance. The most useful financial ratios are those in which the relationship between such attributes is such that the ratio created becomes in itself an important measure of financial performance or condition. To return to the initial example, return on equity, that is, net income divided by shareholders' equity, shows the relationship between funds placed at risk by the shareholders and the returns generated from such funds, and for this reason has emerged as a standard measure of a firm's profitability.

management competence should be considered in the process of evaluating the firm's creditworthiness. Taking it into account, however, is very much a qualitative exercise.

The qualitative and quantitative aspects of credit analysis are summarized in Table 2-2.

## Intermingling of the Qualitative and Quantitative

Certain elements of credit analysis are inherently more qualitative in nature while others are more quantitative (see Table 2-3), although almost always some of both can be found. As previously suggested, the evaluation of a borrower's stand-alone capacity to service debt is, in general, predominately quantitative in nature. Evaluation of its willingness, however, is predominately qualitative in character.

Indeed, practically all facets of credit analysis simultaneously include both quantitative and qualitative elements. A bank's *loan book*, for instance, can be evaluated quantitatively in terms of *nonperforming loan ratios*, but a review of the character of a bank's credit culture and the efficacy of its credit review procedures is, as with an evaluation of management, largely a qualitative exercise. In the same way, those essentially qualitative elements of credit analysis, such as economic and industry conditions, are often amenable, to a greater or lesser degree, to quantitative measurement through statistics such as GDP growth rates or levels of nonperforming loans. Conceptually, any qualitative analysis can reach a degree of quantification, if only through the use of a scoring approach. The qualitative component of quantitative indicators may not always be as obvious. (See the box entitled "The Hidden Qualitative Aspects of Quantitative Measures" on page 50.) Other considerations, such as the degree of ability of the central bank to supervise banks under its authority, are more subjective in nature, but nevertheless comparative surveys on bank regulations or bank failures may function as rough quantitative proxies for this attribute.

## FINANCIAL QUALITY: BRIDGING THE QUANTITATIVE–QUALITATIVE DIVIDE

If corporate credit analysts benefit from an ability to rely more on quantitative analysis, and if financial institution credit analysts benefit from being able to focus on a comparatively homogeneous sector, one area where both face a new challenge is in the analysis of *financial quality.* By financial quality analysis is meant financial evaluation that goes beyond reported numbers to look at the quality of those numbers and the items they are measuring. Consider one aspect of financial quality to which attention has long been given: *asset quality.* To a bank credit analyst, an evaluation of asset quality, the assessment of a bank's loan book, is a critical and traditional part of the analytical process. To a corporate credit analyst, asset quality usually means the value of a firm's inventory, or to a lesser extent, its fixed assets. Financial quality encompasses other financial attributes including earnings quality—how real is the income reported?—and capital quality. If assets are dubious, then by definition, so is the corresponding equity. The all-important matter of liquidity quality in banks has shown its relevance in the long financial crisis that started in 2007, in particular during the subprime crisis of 2008 and the European debt crisis of 2011. These matters are discussed in greater depth later in this chapter.

## Macro and Micro Analysis

The process of bank analysis cannot be done in isolation. Instead, the analyst must be aware of the risk environment of the markets in which the bank is situated and in which it is operating, as well as the economic and business conditions in the financial sector as a whole. In this context, sovereign and systemic concerns must also be taken into account, as must the legal and regulatory environment, and the quality of bank supervision.

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**TABLE 2-2** Qualitative versus Quantitative Credit Analysis

| Quantitative | | Qualitative | |
|---|---|---|---|
| The drawing of inferences from numerical data. Largely equivalent to ratio analysis. Nominally objective. | | The drawing of inferences from criteria not necessarily in numerical form. Nominally subjective. | |
| Requires criteria to be reducible to figures. More amenable to statistical techniques and automation. | | Relies heavily on analyst's perceptions, experience, judgment, reasoning, and intuition. | |
| **Pros** | **Cons** | **Pros** | **Cons** |
| Good starting point for analytical process. | Ignores assumptions and choices that underpin the figures. | Holistic approach that does not ignore what cannot be easily quantified. | Making the relevant distinctions may be difficult—more labor-intensive than quantitative analysis. |
| Permits use of various quantitative techniques. | Numbers may often only approximate economic reality leading to erroneous conclusions. | Takes account of human judgment—does it pass the sniff test? | Works best when analyst is highly skilled and experienced so requires more training and judgment. |
| Shows correlations explicitly. | Ratios may not be answering the relevant questions. | Potentially allows financial vulnerabilities and ill-timed strategies to be identified as early as possible. | May encourage inconsistency in ratings owing to differing individual views of the importance of different factors. |
| Facilitates consistency in evaluation. | Not all elements of credit analysis can be reduced to numbers. | | |

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**TABLE 2-3** Quantitative-Qualitative Matrix

| Element | | Method of Evaluation | Emphasized Evaluation Mode | Mainly Affects |
|---|---|---|---|---|
| Obligor | Capacity<br>Willingness | Financial analysis<br>Reputation, track record | Quantitative<br>Qualitative | PD |
| Conditions<br>Obligation characteristics | | Country/systemic risk analysis<br>Product analysis | Mix<br>Qualitative | All |
| Collateral (credit risk mitigants) | | Appraisal (for collateral) and characteristics of obligation (if a financial collateral); capacity and willingness (for guarantor), etc. | Mix | LGD and EAD |



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**TABLE 2-4** Micro Level versus Macro Level

| **Micro Level Criteria** | | **Macro Level Criteria** | |
|---|---|---|---|
| Found at the individual bank level and in relation to close peers, for example, financial performance, financial condition (liquidity, capital, etc.) management competence | | Found in the operating environment, e.g., market/sectoral trends, sovereign/systemic/legal and regulatory risk, economic and business conditions, industry conditions, government support | |
| **Quantitative** | **Qualitative** | **Quantitative** | **Qualitative** |
| Comparing a bank's earnings and profitability with its peers; observing changes in bank's capital strength over time | Evaluation of bank management, its reputation and business strategy | Establishing correlations between financial variables such as increasing sector loan growth and NPL ratios | Reviewing systemic risk and impact of changes in the business environment—e.g., from new legislation |
| Projecting future changes in financial attributes | Judging the quality of reported results | Noting changes in industry profitability over time; forecasting future changes | Assessing the likelihood of government intervention (support) |

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### THE HIDDEN QUALITATIVE ASPECTS OF QUANTITATIVE MEASURES

Even seemingly quantitative indicators often have a qualitative aspect. In particular, financial ratios are considerably more malleable than may be first assumed. Accounting and regulatory standards, and the scope and detail of disclosure, vary considerably around the world, with the more highly industrialized countries typically maintaining stricter standards. For this reason, analysis of banks in emerging markets frequently requires a greater component of qualitative assessment, since the superficially precise financial disclosure is not always to be trusted.

At the same time, although the foregoing macro-level criteria will influence a bank's credit risk profile, to be of practical use the credit risk of a particular institution must be gauged relative to its previous results and to similar entities. In other words, to rank a bank's comparative credit risk, the analyst needs to judge the bank he or she is appraising with reference both to the bank's own *historical performance* and to its *peers*, while taking account of operating conditions affecting players within and outside of the financial industry. Table 2-4 summarizes the principal micro- and macro-level criteria to be considered in the analytical process.

## An Iterative Process

This said, when looking at a market for the first time, the question arises: *Analyze the individual banks first, or the banking system as a whole?* The analyst confronts something akin to a chicken-and-egg problem. Since individual banks must be viewed in context—that is, in relation to other institutions within the industry, particularly to those similarly situated—the relevant banking system requires an analyst's early attention.

But the system or sector as a whole cannot be fully understood without knowledge about the problems and prospects of specific banks. For example, key ratios such as average loan growth may not be available until a large proportion of the individual banks have been analyzed and the data entered into a system spreadsheet.[17]

To analyze an unfamiliar banking industry, it might be helpful to begin with initial research into the structure of the system as a whole, the characteristics of the industry, and the quality of regulation. In this way, a background understanding of the level and nature of sovereign and country risk may be obtained. This could be followed by a review of the major commercial banks, to provide a foundation and a benchmark for a review of smaller and likely second- and third-tier institutions. Finally, with a more detailed and comprehensive understanding of the sector, the analyst might return to a more macro perspective,

[17] The issue of where to start will be of lesser concern when third-party data providers are used, but there may be occasions when such data is unavailable on a timely basis and sector benchmarks must be established independently.



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preparing a review of the country's entire banking sector, highlighting the impact of key players, and differentiating the various categories of institutions operating within the industry.

## Peer Analysis

It is evident that a comprehensive bank credit analysis incorporates both quantitative and qualitative reviews of the subject bank, and compares it against its peers and with the bank's historical *performance.*[18] The comparison with peers is called *peer analysis*, and the comparison with historical performance is called *trend analysis.* The comparison with peers is undertaken to establish how a bank rates in terms of financial condition and overall creditworthiness among comparable institutions in the banking system.

### WHAT IS A PEER?

The term *peer* is often used in bank credit analysis to refer to an entity of a similar size and character to the entity being examined. It is essentially synonymous with the term "competitor." A peer group might vary in size from 3 institutions to 50 or more. In most cases, however, the number in the group will be between 3 and 15.

Usually, but not always, the institutions will be based in the same jurisdiction. When evaluating mid-sized commercial banks, for example, the peer banks will in most cases be banks of similar size based in the same country. When evaluating institutions having a global reach, the largest investment banks for example, institutions of similar size but based in different countries might be selected.

Finally, when the relevant market includes more than one country, such as Europe, banks of a similar nature, such as Spanish *cajas* and German *Sparkassen* (both forms of regional savings banks) may be compared on a transnational basis. When matching up entities in jurisdictions that have different regulatory regimes, however, care must be taken that such variances—in loan classification, for example—are taken into account.

[18] Although less relevant than it was in the past, the CAMEL model of analysis, introduced later in this chapter, provides a generally accepted framework for analyzing the creditworthiness of banks. CAMEL is an acronym for Capital, Asset quality, Management, Earnings, and Liquidity.

## Resources and Trade-Offs

While time available and the depth of any accompanying written analysis may vary, the analyst's principal tools remain the same. See Table 2-5. It is evident that the volume of resources applied to each type of bank credit analysis will differ according to the analyst's situation and aims, as well as availability.

## Limited Resources

At one end of the spectrum is the bank rating analyst, upon whom the counterparty credit analyst may rely, who will be engaged in the production of independent research based on intensive primary and field research. In addition to examining the bank's annual reports and financial statements, he or she will typically visit the bank, submit a questionnaire to management, and perform a due diligence investigation. In some markets, the United States, for example, the rating agency analyst is permitted access to nonpublic information that is not available to investment and counterparty credit analysts.

### THE BANK VISIT

Bank visits for *due diligence purposes* are most frequently made by rating agency analysts, for which they are a matter of course with regard to the assignment of a rating. Fixed-income analysts, as well as equity analysts, will also frequently visit with bank management, although often such meetings will take place collectively at analysts' meetings conducted by management. These usually coincide with the release of periodic financial statements. Because the evaluation by an agency or fixed-income analyst can have a large impact on the ability of the bank to raise financing, it is generally easier for these analysts to gain access to senior managers than for the counterparty analyst.

Counterparty credit analysts tend to make bank visits less frequently. There are two principal reasons. First, in view of the larger universe of banks that counterparty credit analysts generally cover, they will usually have comparatively little time available to make bank visits. Second, senior bank officers cannot afford to be continually meeting with the hundreds of correspondent banks and other institutions with which they have a relationship. Unless the transaction is an especially important one to the counterparty, the analyst may be relegated to less senior staff, whose role it is to manage correspondent and counterparty banking relationships.



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**TABLE 2-5** Basic Source Materials for Bank Credit Analysis

| Material | Contents | Remarks |
|---|---|---|
| Annual reports | Income statement, balance sheet, and supplementary financial statements. These are generally, but not in all cases, available on the web. If not, they are usually available by request. | Accompanying web-based analyst/investor presentations and press releases may also be a useful source of information. Financial data for a minimum of three years is recommended. |
| Interim financial statements | Interim financials are often limited to an unaudited balance sheet and income statement. | In some jurisdictions, interim statements will only be provided in a condensed or rudimentary form with considerably less detail than in the annual statements. |
| Financial data sources | A variety of electronic database and other search data services may be part of the bank credit analyst's kit. Some key ones include Bankers' Almanac, Bloomberg, and Bankscope. Bankscope, in particular, is widely used by bank credit analysts. It provides re-spread data and ratios drawn from bank end-year and interim financial statements. In addition, a range of informational databases, statistical data sources, credit modeling, and pricing tools are also available from various vendors.* | Although it is always good practice to consult the original financial statements, proprietary data services such as Bankscope are widely employed. Financial data services provide the advantage of consistency in presentation but may not always be available in a timely fashion for all institutions required to be evaluated. In addition, regulatory agencies in various markets may provide data useful to the analyst. In the United States, the Securities and Exchange Commission's EDGAR database is one, while the bank database maintained by the Federal Reserve Bank is another. |
| News services | News articles concerning acquisitions, capital raising, changes in management, and regulatory developments are important to consider in the analysis. Among the most well-known providers of proprietary news databases are Bloomberg, Factiva, and LexisNexis. | Newspaper and magazine clippings can be helpful but are time-consuming to collect; proprietary data services such as *Factiva* function as electronic clipping services and can collect reams of news articles very quickly. Where there is no access to such services, much of the same information can be obtained free of charge from the web. |
| Rating agency reports and other third-party research | Reports from regulatory authorities, rating agencies, and investment banks. Reports from the major rating agencies, Moody's, S&P, and Fitch Ratings, are invaluable sources of information to counterparty credit analysts and fixed-income analysts. | Counterparty credit analysts will necessarily rely to a great extent on rating agency reports when preparing their own reviews. Fixed-income analysts will engage in their own primary research but compare their own findings with those of the agencies in seeking investment opportunities. |
| Prospectuses and offering circulars | Prospectuses and other information prepared for the benefit of prospective investors may include more detailed company and market data than provided in the annual report. | Documents prepared for investors often, as a matter of law or regulation, must enumerate potential risks to which the investment is subject. This can be quite helpful to bank credit analysts. In many jurisdictions, however, prospectuses are not easily accessible or may not add much new data. |
| Notes from the bank visit and third parties | For rating agency analysts, the bank visit is likely to be supplemented by a questionnaire submitted by the agency and completed by the bank. Fixed-income analysts ordinarily will frequently make bank visits. Counterparty credit analysts are likely to make such visits only occasionally. | Banks often prepare a packet of information for rating agency analysts reviewing or assigning a rating. In addition to information formally obtained in the course of a bank visit, the analyst may also seek to obtain informal views about the bank from various sources. |

*Stock and bond prices available from sources such as Bloomberg, which is also a major financial news provider, may also be used for analytical purposes.



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At the spectrum's other end is the counterparty credit analyst assisting in the process of establishing credit limits to particular institutions. Owing to time and resource limitations, he or she is likely to rely largely on secondary source material, such as reports from rating agencies. Visits to institutions will usually be relatively brief and limited to those markets about which the analyst has the greatest concern.[19] In general, the rating agency analyst will engage in primary research to a greater extent while the counterparty credit analyst will depend more heavily on secondary research sources.

## Primary Research

Fundamental to any bank credit analysis are the bank's annual *financial statements*, preferably *audited*[20] and preferably available for the past several years—three to five years is the norm—accompanied by relevant *annual reports*, and any more recent *interim* statements. Other resources may include regulatory filings, *prospectuses, offering circulars*,[21] and other internal or public documents.

As suggested above, thorough primary research would encompass making a visit to the bank in question, preferably to meet with senior management to gain a better understanding of the bank's operating methods, strategy, and the competence of its management and staff.

The bank visit is practically a prerequisite for the rating agency analyst. Where such a due diligence visit is made, the rating agency analyst will almost invariably submit written questions or a questionnaire to the bank, and visit management. Indeed, best practice is for a team of at least two analysts to make a formal visit to the bank, with the visit lasting the better part of a day or more. The exception to this procedure comes in the case of *unsolicited ratings*,[22] which are prepared by the rating agency analyst on the basis of information publicly available. Even for such ratings, the agency analyst may nevertheless visit the institution and have an informal discussion with bank staff. For the bank rating analyst, however, such visits will normally be made whenever possible.[23]

For the counterparty credit analyst, the decision whether to attempt to make a bank visit will naturally be contingent upon the resources available in terms of time and budget, the importance of the relationship with the entity to be analyzed, and the degree of market consensus on the entity's financial condition, as well as the likelihood that significant information will be gleaned from such a visit. As would be expected, managers at the bank to be evaluated must themselves be receptive to a visit.

[19] In effect, by relying on external rating agencies, the counterparty analyst is outsourcing part of the credit function. Regulatory considerations may also come into play. Reference to the opinion of independent agencies may be required to satisfy rules governing the extension of credit or the making of investments at the organization at which the analyst is employed. Conversely, however, where the employing bank utilizes an internal rating-based approach to allocating capital, the use of an internal rating system that is independent of external agency rating assignments may be an element of regulatory compliance.

[20] The adjective *preferably* is inserted here only because in some emerging markets, recent audited financial statements may be impossible to obtain, particularly in regard to state-owned institutions; and a trade-off surfaces between taking account only of audited data that is out of date and considering unaudited data that is current. Where government support is the primary basis for the creditworthiness of the entity, the use of unaudited data may shed additional light on the organization's performance. However, organizational credit policies may prohibit the use of unaudited data, and as a general rule unaudited data should not be used. Moreover, the absence of audited data in itself may fairly be regarded as an unfavorable credit indicator.

[21] Offering circulars and prospectuses are documents prepared in advance of a securities offering to inform prospective investors concerning the terms of the offering. Information concerning the issuer, its activities, and notable risks is typically included in these documents. Often, the format and content of such documents will be governed by regulation.

[22] Unsolicited ratings are assigned by an agency on its own initiative, either on a gratis basis or without a formal agreement between the agency and the issuer or counterparty. When the rating industry began in the United States in the early twentieth century, all ratings were unsolicited. The rating agencies relied on subscription revenue from investors to support their operations and generate a profit. As the industry became established, however, an external rating effectively became a prerequisite to a successful debt issue. The rating agencies were then in a position to charge issuers for a rating. Such paid-for ratings are called solicited ratings, and have become the norm among the major global rating agencies. Nevertheless, unsolicited ratings still exist, particularly outside of major markets or in respect of companies that do not issue significant debt, but which are of interest to investors and counterparties. Publicly available information provides the basis for such ratings.

[23] Note that unless the analyst is working in the capacity of bank examiner, there is normally no right of access to bank management. When performing a solicited (i.e., paid) rating, rating agencies will ordinarily enter into an agreement that ensures analyst access to management. Otherwise, such visits are made on a courtesy basis only, and in exceptional cases the analyst may be unable to meet in person with management. In-house analysts, in particular, may have difficulty or may be shunted off to the investor relations or correspondent bank relations staff who often will be able to add little to the data provided in the bank's annual report.



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## REQUISITE DATA FOR THE BANK CREDIT ANALYSIS

The items needed to perform a bank credit analysis will depend upon the nature of the assignment undertaken, but in general the following resources should be reviewed:

- The annual report, including the auditor's report, the financial statements and supplementary information, as well as interim financial statements
- Financial data services and news services
- Rating agencies, data from regulators, and other research sources
- Notes from primary and field research

### The Annual Report

Although the annual report may be full of glossy photos and what appears to be corporate propaganda, it should not be ignored. Much can be learned from it about the culture of the bank, how the bank views business and economic conditions, and management's strategy. As the annual report is prepared for the bank's shareholders and prospective equity investors, its thrust will be on putting the bank's operating performance in the best possible light. Bearing this in mind, an understanding of the management's side of the story can nevertheless provide a useful counterpoint to a more critical examination of bank performance.

In addition to the intangible impressions it may engender, the bank's annual report will sometimes supply information on particular aspects of the bank's operations not available in the financial statements. Not infrequently it may contain a wealth of mundane factual information, such as the institution's history and the number of branches and employees, as well as useful industry and economic data. Similarly, significant information relating to the regulatory environment, such as changes in accounting rules or banking laws, can frequently be found in the annual report.

> **READING BETWEEN THE LINES**
>
> When reading a company's annual report, the analyst should ask himself or herself, "What points are being glossed over?" If liquidity appears to be a weak point, how does the company treat this issue? Is the concern addressed, or is it mentioned only in passing? What other scenarios might unfold besides management's rosy view of their firm's future?

### The Auditor's Report or Statement

The analyst should turn to the auditor's report at the start of the analysis to determine whether or not the auditor of the bank's accounts provided it with a clean or *unqualified opinion.*[24] The auditor's report will normally appear just prior to the financial statements. In essence, a *clean opinion* communicates that the auditor does not disagree with the financial statements presented by management. It does not mean that the auditor might not have presented the financial information differently, choosing a different accounting approach or disclosing additional data. In other words, an unqualified opinion means that the financial statements as presented meet at least the minimum acceptable standards of presentation.[25]

### Content and Meaning of the Auditor's Opinion

The auditor's opinions vary somewhat in length and content depending upon the jurisdiction in which the audit was performed and the standards applied. Much of the content will be boilerplate language used as a standard format, and designed primarily to shield the auditor from any legal liability.[26] What is important is to watch out for any language that is *out of the ordinary.* A typical unqualified auditor's report will contain phrases more or less equivalent to those in Table 2-6.[27]

As a reading of the table will make clear, a clean auditor's report does not ensure against fraud or misrepresentation by the company audited. The fairly standardized language of the auditor's report, although varying from country to country, has evolved to emphasize the limitations in what

[24] "Unqualified" means that the auditor has attached no additional conditions to its opinion, that is, the opinion is without further qualification.

[25] John A. Tracy, *How to Read a Financial Report: for Managers, Entrepreneurs, Lenders, Lawyers and Investors*, 5th ed. (New York: John Wiley & Sons, 1999).

[26] In other words, the language is largely intended to provide a defense against litigation that would seek to hold the auditor liable for any fraud or misrepresentation subsequently discovered in the financial statements.

[27] The vernacular translations supplied for each statement are the interpretations of the authors and, needless to say, have no official standing.



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**TABLE 2-6** The Auditor's Opinion: An Unofficial Translation Guide

| Boilerplate | What this means: |
|---|---|
| The auditors have audited specified financial statements of a certain date. | "Do not blame us, the auditors, for anything that occurred or became apparent after that date." |
| Financial statements are the responsibility of the management of the company. | "We can only base our opinion on data provided by the company. If the data is inaccurate or fraudulent, blame company management, not us." |
| The financial statements have been prepared in accordance with generally accepted local accounting standards and are free from material misstatement. | "The financial disclosure provided meets minimally acceptable local accounting standards or relevant regulations governing such disclosure. We have not detected any egregious errors or inaccuracies that are likely to have a major impact on any conclusion you may draw about the company for investment purposes." |
| The audit involved examining evidence supporting the statements on a test basis, which provide a reasonable basis for the auditor's opinion. | "We have not scrutinized every single item of financial data or even most of them. This would cost a small fortune and take an exceedingly long time. Instead, as is deemed customary and reasonable in our profession, we have tested some data for discrepancies that might indicate material error or fraud." |
| In the opinion of the auditors, the financial statements present that financial position fairly in all material respects as of the date of the audit. | "The financial statements might not be perfect, but they present a reasonable picture of the company's financial condition, subject to the present standards set forth in law and generally followed in the industry, notwithstanding that higher standards might better serve investors." |

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should be drawn from it. Although audits could arguably be more thorough, the expense involved in checking most or all of the source data that make up a company's financial statements other than on a test basis has been reasonably asserted to be prohibitive.

## Qualified Opinions

A *qualified opinion*, that is, one in which the auditors limit or qualify in some way their opinion that the financial statements provide a fair representation of the bank's financial condition, can be discerned in cases where additional items other than those mentioned above are added. A qualified opinion is easily identifiable by the presence of the word *except* in the auditor's statement or report. It is typically found in the concluding paragraph which usually starts with "In our opinion."

Typical situations in which an opinion will be qualified by the auditors include the following:

- The existence of unusual conditions or an event that may have a material impact on the bank's business
- The existence of material related-party transactions
- A change in accounting methods
- A specific aspect of the financial reports that is deemed by the auditor to be out of line with best practice
- Substantial doubt about the bank's ability to continue as a going concern

Of course, the last type of qualification is the most grave and will justifiably give rise to concern on the part of the analyst. Not all qualifications are so serious and should be considered bearing in mind what else is known about the bank's condition and prospects, as well as the prevailing business environment. An extremely rare phenomenon is the adverse opinion, in which the auditors set forth their opinion that the financial statements do not provide a fair picture of the bank's financial condition.

Philippine National Bank, as an example, attracted a serious qualification from its auditors in 2004 in a situation where a specific aspect of the financial reports was deemed to be irregular.

Although most auditors' opinions are unqualified and therefore generally do not provide any useful information about the bank, a qualified opinion is a red flag even if it is phrased in diplomatic language, and even if the bank can hide behind the leniency of some regulation. The



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## CASE STUDY: THE AUDITOR'S OPINION: THE CASE OF PHILIPPINE NATIONAL BANK

Consider the case of Philippine National Bank (PNB), one of the banks in the Philippines—but which is not the central bank of the country—that were hardest hit by the Asian financial crisis of 1997. The auditor, SGV & Co., said in the last paragraph of the 2004 annual report: "In our opinion, except for the effects on the 2004 financial statements of the matters discussed in the third paragraph, the financial statements referred to above present fairly in all material respects the financial position of the Group and the parent company as of December 31, 2004 and 2003, and the results of their operations and their cash flows for each of the three years in the period ended December 31, 2004, in conformity with accounting principles generally accepted in the Philippines."

In the third paragraph, the auditor described a transaction involving PNB's sale of nonperforming assets to a special-purpose vehicle. The losses from the sale of the transaction were deferred over a 10-year period in accordance with regulatory accounting principles prescribed by the Philippine central bank[28] for banks and other financial institutions availing of certain incentives established under the law. But SGV & Co. noted that had such losses been charged against current operations, as required by generally accepted accounting principles, investment securities holdings, deferred charges, and capital funds as of December 31, 2004, would have decreased by P1.9 billion, P1.1 billion, and P3.0 billion, respectively, and net income in 2004 would have decreased by P3.0 billion. This would have been taken against a posted net income of about P0.35 billion in 2004.

In his report on the 2010 accounts, the auditor still had to qualify his opinion as the reporting of the transaction did not comply with the rules of the Philippine GAAP for banks. This is not, of course, to say that the bank was doing anything illegal or was attempting to conceal the transaction.

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irregularities noted should be closely scrutinized for their impact on financial reporting.

## Change in Auditors

Like a poor credit rating, a *qualified opinion* is not something a company's management wants to see. As it is management who generally selects and pays the auditing firm, it is sometimes not unreasonably perceived that when a company changes auditors it is the result of a disagreement about the presentation of financial statements or because the particular accounting firm is unwilling to provide a clean opinion. This is certainly not always the case, and the reasons for a change in auditor may be entirely different. In some countries, a change in auditors after a period of several years is mandatory, as a means of preventing too cozy a relationship developing between the auditor and the audited company. Nonetheless, changes in auditors should be noted by the analyst for possible further inquiry.

## Who Is the Auditor?

Finally, mention should be made of the organizations that perform audits. The accounting profession has consolidated globally into a few major firms.[29] In some countries, however, independent local firms may have most or all domestic banks as their clients. While privately owned banks are usually audited by independent accounting firms, government banks sometimes are not. Special government audit units may perform the audit, or they may not be audited at all.

Although there may be no significant difference in quality vis-à-vis a less well-known firm, an audit by one of the major international accounting firms may be perceived as affording a certain imprimatur on a bank's financial statements. The critical issue from the analyst's perspective should not be the name of the firm, but whether the auditor has the expertise to scrutinize the enterprise in question. Bank accounting, for instance, differs in some key respects from corporate accounting, and a modicum of comfort can be drawn from an audit performed by a firm that has experience with financial institutions. Another point to keep in mind is that some local auditors might carry an internationally renowned brand name under arrangements that do not include following all technical and ethical rules in place within that international audit firm.

[28] In spite of its name, Philippine National Bank is not the central bank. The central bank is Central Bank of the Philippines or Bangko Sentral ng Pilipinas.

[29] Note that the large global accounting firms often operate through local affiliates that often have names different from their global affiliates.



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## The Financial Statements: Annual and Interim

The essential prerequisite to performing a credit analysis of a bank, or indeed any company or separate financial entity, is access to its financial statements, either in original form or prespread into a format suitable for analytical purposes.[30] Without such financial data, quantitative analysis will be practically impossible.

There are three primary financial statements:

1. The balance sheet—to include off-balance-sheet items
2. The income statement
3. The statement of cash flows

Of these, the balance sheet and the income statement are by far the most important to the analysis of banks.

In respect to nonfinancial companies, the statement of cash flows is often considered to be the most important. The cash flow statement is not particularly helpful, though, in bank credit analysis.

A fourth financial statement, *the statement of changes in capital funds*, is useful in both financial company and nonfinancial company credit analysis. When available, it is particularly helpful in bank credit analysis, as it clearly shows changes in the capital levels reported by the institution.[31]

### FINANCIALS

Sometimes referred to as *financials, financial statements* are a form of published accounts that show a company's *financial condition* and performance. There are three principal financial statements:

1. The *balance sheet* (also called *the statement of condition*)
2. The *income statement* (also called the *profit and loss statement* or *P&L*)
3. The *statement of cash flows (cash flow statement)*

Other financial statements may be published of which perhaps the most common is the *statement of change in capital funds (the statement of changes in shareholders' equity).* To facilitate the analytical process, the reports published by companies will usually be modified, or *re-spread,* to present the financial data in a consistent manner across the sector so that like items can be compared with like items.

*Audited* financial statements will ordinarily be found in a company's *annual report* together with the *auditor's report*, *supplementary footnotes*, and a report from management, the last of which may take a variety of forms (e.g., Chairman's Letter to Shareholders). Depending upon the jurisdiction and applicable rules, a company may issue interim financial statements semiannually or quarterly. Of course, for internal or regulatory purposes, special financial statements, normally unaudited, may be prepared.

## Timeliness of Financial Reporting

The more timely the financial statements, the more useful they are in painting a picture of an institution's current financial condition. Unfortunately, not all banks issue their annual reports as soon as might be preferred. At best, publication of annual reports will follow within one to two months following the end of the financial year. On occasion, extraordinary circumstances such as the need to restate[32] figures as the result of a regulatory action may delay publication. This is usually not a positive sign.

In other circumstances, the reasons for late publication are more innocuous. The bank may still be in the process of translating the report into another language, or there may be delays in printing. In such cases, depending upon the purpose and urgency of the review, the analyst might attempt to obtain preliminary or unaudited figures directly from management.

As a rule of thumb, the less developed the market, the longer the delay in the publication of financial reports tends to be. The most dilatory in reporting financial data tend to be banks in emerging markets that are either government-owned institutions or are not publicly listed on a stock exchange. In extreme cases, an interval of up to two years may pass following the end of fiscal year before audited or official financial data are available for state-owned banks. It is evident that in such cases, the value

[30] It is assumed that readers will have some degree of understanding of accounting principles, if not an accounting background.

[31] The statement of changes in capital funds is sometimes reported in combination with one of the other statements, and at other times it is reported separately. In some markets, it may be omitted entirely.

[32] Restated financial statements (restatements), also called restatement of prior-period financial statements, are adjusted and republished to correct material errors in prior financial statements or to revise previous financial statements to reflect subsequent changes in an entity's accounting or reporting standards.



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of the reports will almost certainly be very limited.[33] Still, some data is better than none and can at least provide the basis for a less than laudatory report.

## SPREADING THE FINANCIALS

While the evaluation of the creditworthiness of a bank is, as suggested, both a quantitative and a qualitative endeavor, an examination of the quantitative financial attributes of the institution is usually the first stage in forming a view concerning its overall credit quality. In this section, therefore, a bit more emphasis is placed on preparing to engage in the quantitative part of the analytical process. The initial step in this first stage, unsurprisingly, is to examine a bank's financial statements.

### Making Financial Statements Comparable

At the outset, we confront an obstacle that is not unique to the banking industry. In any given market, it is rarely the case that all banks, or all nonfinancial firms, for that matter, will adhere to any single standard format of account presentation. Instead, there is a great deal of variation in how banks present their accounts. While the key elements of published bank accounts tend to be arranged in a similar fashion, the proverbial devil lies in the details. Though guided by regulatory requirements—which have improved in recent times—and the advice of their auditing firm, each bank management will present its results according to its own preferences.

Classification of particular line items and the level of disclosure will differ, as will the lucidity of the accompanying notes and explanatory material. Some financial statements provide extremely detailed data; others are more cursory. Likewise, some provide a great deal of useful information in the financial statements themselves; others relegate data of interest to the accounting notes. Finally, some can be clearly understood, and others can be aggravatingly opaque. Were an analyst to proceed to examine a set of banks solely with reference to the financial statements released by management together with their annual reports, the exercise would be fraught with difficulties. Owing to variations in disclosure, presentation, and classification, he or she would be constantly turning pages back and forth, checking definitions, and adjusting for differences in disclosure or categorization. Obtaining a clear picture of how each bank stacks up against others in the sector could be more frustrating than necessary.

To simplify the analytical process and reduce the risk of error, it is common practice to arrange the financials of the banks to be analyzed on a spreadsheet in a simplified and consistent manner, so that like items can be more easily compared with like items. This process is called *spreading the financials.* The analyst's initial task therefore is to spread the financials to present the bank's accounts consistently to facilitate their comparison. With the key financial data presented consistently, the analyst's next steps are to derive those ratios that will provide the best indication of the financial performance and condition of the bank and to collect the facts and information to be used to render the requisite qualitative judgments as part of the analytical process.

### DIY or External Provider

Spreading the data may be done in any number of ways. On the one hand, the process may be highly automated through links to internal or proprietary databases. In the case of banks, the leading product in the field is Bankscope, which is ubiquitous in counterparty credit departments around the world, although there are, of course, other sources. On the other hand, the analyst may need to convert the financial data independently provided by each bank into the format decided upon. The format itself may be prespecified, or it may be left up to the analyst's discretion. Naturally, even when a format is specified, the analyst may use his or her own working calculations to supplement the formal procedure.

An advantage of spreading one's own financials is that by completing the process the analyst has already learned

[33] Where the subject institution is wholly owned by the national government, its credit risk may at times be found to be essentially equivalent to sovereign risk. In this situation, the standalone financial strength of the bank would be a secondary consideration and the delay in financial reporting less critical than it otherwise would be.

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quite a bit about the bank, and is well on the road to preparing a report. Spreading financials requires an understanding of how the bank has characterized various items on the accounts, and in the process of making adjustments to fit the standardized spreadsheet, the analyst will glean a great deal of insight into the nature of the bank's activities and the performance of its business. Another advantage is that external data providers are not infallible and may, either as a result of policy or error, characterize particular items in a nonoptimal manner, and occasionally in a manner that can give a misleading impression. Where the analysis is of both a critical and intensive nature, rather than one that is routine, there is really no substitute for preparing one's own spreads. Finally, where the requisite data are not available from a third-party provider, spreading one's own financials will be the only alternative.

The primary disadvantage to spreading financials independently is that it is often highly time-consuming and tedious work. In some cases, the accounts may be in a foreign language, further complicating matters. Moreover, the analyst's workload, particularly the time allotted for each evaluation, may make spreading the data from scratch impractical. Having all the data available through an external provider in a standardized format obviously speeds up the review process and enables the analyst to get on with making comparisons rather than spending a great deal of time re-entering data and deciphering items that may be irrelevant to the final review. With regard to an analytical team as a whole, the use of an external provider (or an internally maintained database) is likely to encourage a greater level of consistency in how the data are spread, absent close supervision of analysts, since the format used by the data provider will be the same for each.

One has to recognize, though, that external providers are faced with the same problem as an analyst who performs his own data spreading: they sometimes have to take a view as to how some items should be split into separate subitems, or to the contrary as to how several items should be combined into a single one. While banks in advanced economies have little freedom in the way they publish their figures, the situation could be different in emerging markets. As a result, good analysts might use external providers' data as a basis, but would always revisit the matter through a direct study of raw data published by the bank.

## One Approach to Spreading

Assuming no formal procedure is in place, it is a fairly simple matter to prepare a spreadsheet for the key data to be entered. Those skilled in manipulating Microsoft Excel and similar programs, of course, can build customized spreadsheets that are highly automated and include built-in analytical tools. Table 2-7 contains a very simplified version of a uniform spreadsheet that might be used for bank analysis. In this condensed version, we have only shown one year of financial data, and have also included formulas for the reader's reference, but comparisons across years are easily derived. While we have not yet discussed the particular financial attributes that the bank credit analyst seeks to evaluate, the illustration may perhaps serve nevertheless as a reference point.

It is important to note that a number of indicators cannot directly be derived from such a financial spreadsheet, as some figures are simply not disclosed by financial institutions, or when disclosed are not sufficiently transparent.

At the upper left of the spreadsheet, descriptive information is provided concerning the institution, which in this case is a hypothetical name, "Anybank." The left side of the spreadsheet shows a condensed income statement for Anybank, while the right side contains a condensed balance sheet. The far left-hand column shows how each line item in the income statement is derived, and the column to the right of it describes the line item. For example, interest income is designated as "A," interest expense as "B," and net interest income "C" is therefore defined as A−B. The third column from the left shows amounts for each item. The right side of the spreadsheet showing assets, liabilities, and equity is analogous to the income statement on the left, with the item defined in the left-hand column (fourth from the left margin of the spreadsheet), the item description in the middle column, and the amount in the far right-hand column.



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**TABLE 2-7** Simplified Uniform Spreadsheet for Bank Analysis

| **Bank Name:**<br>**Location:**<br>**Period:** | **ANYBANK**<br>**ANYTOWN, ANYLAND**<br>**Fiscal Year Ending: 12/31/ (Consolidated)** | **200X** | **Currency** | **ANYUNIT, millions** | **200X** |
|---|---|---|---|---|---|
| Definitions | INCOME STATEMENT | | Definitions | BALANCE SHEET—ASSETS | |
| A | Interest Income | 5000 | a | Cash and Near Cash | 2400 |
| B | Interest Expense | 1000 | b | Interbank Assets | 1800 |
| C=A−B | Net Interest Income | 5000 | c | Government Securities | 3600 |
| D=E+F | Noninterest Income | 3000 | d | Marketable Securities | 3000 |
| E | Fees and Commission Income | 2000 | e | Unquoted Securities | 200 |
| F | FX and Trading Accounts | 1000 | f | Total Loans and Advances | 171400 |
| G=C+D | Operating Income | 8000 | g | Due from Holding and Subsidiaries | 0 |
| H=I+J+K | Noninterest Expense (Operating Expense) | 4000 | h=sum(b[i]:g) | Total Earning Assets | 180000 |
| I | Compensation and Fringe Benefits | 2500 | i | Average Earning Assets | 177500 |
| J | Occupancy Expenses | 500 | j | Subsidiaries and Affiliates | 0 |
| K | Other Expenses | 1000 | k | Fixed Assets | 20000 |
| L=G−H | Preprovision Income (PPI) | 4000 | l | Other Assets | 0 |
| M | Loan Loss Provision (LLPs) | 500 | m | Intangible Assets | 0 |
| N=L−M | Net Operating Income after LLPs (NOPAP) | 3500 | n=a+h+j+k+l | Total Assets | 200000 |
| O | Nonoperating Items | 0 | | BALANCE SHEET—LIABILITIES and CAPITAL | |
| P=N−O | Pretax Profit (excluding[ii] nonoperating items) | 3500 | o | Interbank Deposits | 4600 |
| Q | Tax | 1200 | p | Customer Deposits—Demand | 110000 |
| R=P−Q | Net Income before Minority Interest | 2300 | q | Customer Deposits—Svgs and Time | 55000 |
| S | Minority Interest | 200 | r=p+q | Total Customer Deposits | 165000 |
| T | Preferred Dividends | 100 | s | Due to Holding and Subsidiaries | 0 |
| U=R−S−T | Net Income Attributable to Common Shareholders | 2000 | t | Other Liabilities | 15400 |
| | | | u=sum(o:tl) | Total Liabilities | 185000 |
| V | Common Dividends | 800 | v | Subordinated Debt and Loan Capital | 0 |
| W=U−V | Retained Earnings | 1200 | w | Minority Interest in Subsidiaries | 0 |



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| | | | | | |
|---|---|---|---|---|---|
| | RATIOS | | | Shareholders' Equity | 15000 |
| | PROFITABILITY | | | CAPITAL | |
| X=R/aa | Return on Assets | 1.16% | y | Tier 1 Capital | 15000 |
| Y=R/z | Return on Equity | 15.86% | z | Average Equity | 14500 |
| Z=C/I | Net Interest Margin | na | aa | Average Assets | 197500 |
| ZA=H/G | Efficiency Ratio | | ab | Contingent Accounts | 0 |
| ZB=H/aa | Cost Margin | | ac | Risk-Adjusted Capital | 15000 |
| ZC | Effective Tax Rate, Reported | | ad | Risk-Weighted Assets | 180000 |
| ZD=R/ad | Return on Risk-Weighted Assets | | ae | Tier 2 Capital | 0 |
| | CAPITAL ADEQUACY | | | LOAN BOOK—ASSET QUALITY ITEMS | |
| ba=z/aa | Equity/Assets (Avg) | 7.34% | af | Net Charge-Offs (NCOs) | 200 |
| bb=z/I | Equity/Earning Assets (Avg) | 8.45% | ag | LLRs | 1800 |
| bc=x/f | Equity/Loans | 8.75% | ah | Nonperforming Loans | 1000 |
| | *BIS Risk-Adjusted Capital Ratios:* | | ai | 90-Day Past Due and Accruing (i.e., not counted as official NPL)[iii] | 20 |
| bd=y/ad | Tier I | 8.06% | | | |
| be=ae/ad | Tier II | 0.00% | aj | Restructured Loans | 50 |
| bf=ac/ad | BIS Total | 8.06% | ak | Other Real Estate Owned (OREO)[iv] | 100 |
| bg=n/x | Leverage (times) | 13.3 | al=sum(ah:ak) | Nonperforming Assets | 1170 |
| | LIQUIDITY[v] | | | ASSET QUALITY RATIOS | |
| bh=f/n | Loans/Assets | 85.70% | am=l/f | LLPs/NCOs | 250.0% |
| bi=f/r | Loans/(Customer) Deposits | 103.88% | an=ag/f | Loan Loss Reserves/Gross Loans | 1.1% |
| bj=f/(r+o) | Loans/Total Deposits | 101.06% | ao=am/(f+ak) | NPAs/Loans + Other Real Estate Owned | 0.7% |
| bj=b/n | Interbank Assets/Assets | 0.90% | ap=am/f | NPAs/Loans | 0.7% |
| bk=b/o | Interbank Assets/Interbank Deposits | 39.13% | aq=ag/ah | Loan Loss Reserves/Nonperforming Loans | 180.0% |
| bl=(a+b+c+d)/n | Quasi-Liquid Assets Ratio | 5.40% | ar=am/x | NPAs/Total Equity | 7.8% |
| bm=(a+b+c)/n | Liquid Assets Ratio | 2.10% | as=ag/f | LLRs/Loans | 1.1% |

i. Depending upon the definitions used, some cash/near cash items might be deemed to be "earning assets."

ii. In contrast to usual reporting practice, for analytical purposes nonoperating items may be subtracted before calculating pretax profit or net income.

iii. For reasons of space, special mention items (that is, problematic assets that do not meet aging criteria) are not shown. In some circumstances special mention items would not be considered official or technical NPLs and might be broken out as a separate line item. This line item hence could be regarded as official NPLs (meeting aging criteria) but nevertheless accruing (by reason of the bank's judgment) minus special mention items (nonofficial NPLs deemed by the bank to be problematic).

iv. This line refers to foreclosed assets.

v. Analytical definitions of liquid assets would likely subject category "c" to a liquidity check taking account of local conditions and any formal restrictions on negotiability.

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## ADDITIONAL RESOURCES

### The Bank Website

The advent of the Internet has made the bank credit analyst's job easier.[34] No longer is it always necessary to request a bank's annual report and wait weeks for its arrival. Annual reports, financial statements, news releases, and a great deal of background information on the bank and its franchise can be obtained from the web. Moreover, the depth, interactivity, and overall quality and style of the site will say something about the bank as well as its online strategy. In addition, many banks will post webcasts of their results discussion with analysts together with the accompanying presentation.

### News, the Internet, and Securities Pricing Data

Annual reports are just about out-of-date the day they are published. Much can happen between the end of the financial year and the publication of the annual report, and the analyst should run a check to see if any material developments have occurred. An examination of the bank's website can be very helpful here, but alternatively, a web search or the use of proprietary electronic data services such as *Bloomberg*, *Factiva*, or *LexisNexis* can be extremely valuable in turning up changes in the bank's status, news of mergers or acquisitions, changes in capital structure, new regulations, or recent developments in the bank's operations.

Bond pricing will, of course, be a primary concern of the fixed-income analyst, but counterparty credit and rating agency analysts can make constructive use of both bond and equity price data when the bank is publicly listed or is an issuer in the debt markets. Anomalous changes in the prices of the bank's securities can herald potential risks. The market will be the first to pick up news affecting the price of the bank's securities, and in this sense, it can function as a kind of early-warning device to in-house and agency analysts.[35] Real-time securities data in emerging markets, as provided by Bloomberg, for example, can be costly, but then again the web with the emergence of search engines like Google has leveled the playing field making much of the same or similar business and financial news easy to access.

### Prospectuses and Regulatory Filings

Prospectuses and offering circulars intended for prospective investors are published to enable them to better evaluate a potential investment. Generally speaking, their format and content is restricted by regulation to compel securities issuers to present the benefits of the investment in a highly conservative manner and to highlight possible risks. In view of this latter objective, these documents can be, but are not always, rich sources of information about a bank. Their value depends a great deal on the market and upon the type of securities issue for which the prospectus was prepared. Prospectuses for equity and international debt issues may add substantial data beyond what was included in the latest annual report. In contrast, prospectuses for bank loan syndications and local bond issues may provide relatively little helpful information. Prospectuses, however, are not always easily accessible.[36] Ongoing regulatory filings made with the securities regulator have a similar function, although they are intended to benefit buyers in the secondary market as well as the purchasers of new issues.

### Secondary Analysis: Reports by Rating Agencies, Regulators, and Investment Banks

The use of secondary research will depend on the type of bank credit report being prepared. Rating agency analysts will often review official reports from central banks and government regulators, but, like fixed-income analysts, will avoid the use of competitor publications.

[34] The pervasive publication of annual reports and financial statements on the World Wide Web has been a great boon to credit analysts generally and considerably reduced problems in obtaining financial data in a timely manner. Consolidation in the financial services industry together with the ubiquity of third-party data providers—most notably Bankscope mentioned earlier—has facilitated the bank analyst's work by reducing the time spent on collecting and entering data. Nevertheless, there are some institutions that do not make their financial reports freely available through these channels. In such cases, there may be no alternative but to contact the bank directly and request that they be posted, e-mailed, or faxed as the case may be.

[35] One should not read too much in such signals.

[36] Some prospectuses may be available from online data providers on a subscription basis.



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## CAMEL, CAMELS, AND CAMELOT

The acronym CAMEL can also function as a mnemonic as illustrated in the list on this page. With no disrespect intended to the animal, the two humps on the camel that provide reserves of nourishment can be thought of as signifying C for capital and L for liquidity, both of which provide a bank with the reserve buffer necessary to absorb economic shocks. The animal's front legs pull it forward as do a bank's earnings, so long as they are not hindered by asset quality problems coming from behind. Finally, the camel's head and eyes, which scan the desert horizon for the next oasis or dust storm, could stand for bank management. It is management's job to ensure the institution's survival by obtaining the necessary sustenance while avoiding the perils that may befall it, particularly in turbulent times.

In addition to the acronym CAMEL, another widespread variant, CAMELS adds an "S" for sensitivity to market risk. This was officially adopted by the Uniform Financial Institutions Rating System (UFIRS) in 1997.

Under the UFIRS, the regulatory agencies evaluate and rate a bank's financial condition, operational controls, and compliance in six areas. These areas are Capital, Asset Quality, Management, Earnings, Liquidity, and Sensitivity to market risk. Each of these components is viewed separately and together to provide a summary picture of a bank's financial soundness.

The CAMEL model is also used in equity analysis. A variant termed CAMELOT, developed by Roy Ramos at investment bank Goldman Sachs (GS), added an "O" and "T" to the basic CAMEL root to represent evaluation of the bank's operating environment and assessment of transparency and disclosure.

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Bank counterparty credit analysts, however, will rely to a greater extent on secondary research sources and less on primary sources. Their credit reviews are not intended for external publication, and the views of the rating agencies are not usually ignored. Investment reports prepared by equity analysts, although they take a different perspective from bank credit reports, can nevertheless be useful in helping to form a view concerning a bank. Since these reports are ordinarily prepared for their investor-customers, very recent ones may not be easy to obtain. Such reports may be purchased, sometimes on an embargoed basis, from services such as those offered by Thomson Reuters.[37]

## CAMEL IN A NUTSHELL

Once all information, including an appropriate spreadsheet of the financials over several years, is available to them, bank credit analysts almost universally employ the CAMEL system or a variant when evaluating bank credit risk. Although originally developed by U.S. bank supervisors in the late 1970s as a tool for bank examination,[38] it has been widely adopted by all rating agencies and counterparty analysts. Even many equity analysts draw on the CAMEL system to help them in making recommendations concerning the valuation of bank stocks. It is the approach we reluctantly explain in this chapter.[39]

What is the CAMEL system? CAMEL is an oversimplification that does not catch all it should, and that does not give proper weight to the various elements. CAMEL is simply an acronym that stands for the five most important attributes of bank financial health. The five elements are:

C for Capital
A for Asset Quality
M for Management
E for Earnings
L for Liquidity

[37] Selected reports also may be available to Bloomberg or Factiva subscribers.

[38] Under the Uniform Financial Institutions Rating System adopted in the United States in 1979, the CAMELS system was formally adopted as the most comprehensive and uniform approach to assessing the soundness of banks, although as a formalized methodological approach appears to date back to the practices of bank examiners in the early twentieth century.

[39] It should be emphasized, however, that the financial services industry is rapidly evolving as banks engage in new activities. Refinements and alternative models to bank credit assessment methodologies, therefore, cannot be ignored.



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All but the assessment of the quality of "management" are amenable to ratio analysis, but it must be emphasized that "liquidity" is very difficult to quantify.

Since the term CAMEL was coined, banks have ventured into a number of types of transactions that no longer fit into those five categories. Many such transactions are recorded off the balance sheet or, if they are recorded on the balance sheet, are prompted by asset/liability management needs, making the term *asset quality* too restrictive. But a camel would no longer be a camel without its "a" or with too many additional letters.

Although sometimes termed a model, the CAMEL system is really more of a checklist of the attributes of a bank that are viewed as critical in evaluating its financial performance and condition. Nevertheless, it can provide the basis for more systematic approaches to evaluating bank creditworthiness.

As used by bank regulators in the United States, the CAMEL system functions as a scoring model. Institutions are assigned a score between "1" (best) and "5" (worst) by bank examiners for each letter in the acronym. Scores on each attribute are aggregated to form composite scores, and scores of 3 or higher are viewed as unsatisfactory and draw regulatory scrutiny.

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# Classifications and Key Concepts of Credit Risk

# 3

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## Learning Objectives

After completing this reading you should be able to:

- Describe the role of ratings in credit risk management.
- Describe classifications of credit risk and their correlation with other financial risks.
- Define default risk, recovery risk, exposure risk, and calculate exposure at default.
- Explain expected loss, unexpected loss, VaR, and concentration risk, and describe the differences among them.
- Evaluate the marginal contribution to portfolio unexpected loss.
- Define risk-adjusted pricing and determine risk-adjusted return on risk-adjusted capital (RARORAC).

*Excerpt is Chapter 2,* Developing, Validating and Using Internal Ratings: Methodologies and Case Studies, by *Giacomo De Laurentis, Renata Maino and Luca Molteni.*

*See bibliography on pp. 515–518.*



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## CLASSIFICATION

### Default Mode and Value-Based Valuations

Credit risk can be analyzed and measured from different perspectives. Table 3-1 shows a classification of diverse credit risk concepts. Each of the listed risks depends on specific circumstances. Default risk (also called counterparty risk, borrower risk and so forth, with minor differences in meaning) is an event related to the borrower's default. Recovery risk is related to the possibility that, in the event of default, the recovered amount is lower than the full amount due. Exposure risk is linked to the possible increase in the exposure at the time of default compared to the current exposure. A default-mode valuation (sometimes also referred to as 'loss-based valuation') considers all these three risks.

However, there are other relevant sources of potential losses over the loan's life. If we can sell assets exposed to credit risk (such as available-for-sale positions), we also have to take into account that the credit quality could possibly change over time and, consequently, the market value. Credit quality change is usually indicated by a rating migration; hence this risk is known as 'migration risk'.

In the new accounting principles (IAS 39), introduced in November 2009 by the International Accounting Standard Board (IASB), the amortized cost of financial instruments and impairment of 'loans and receivables' and of 'held-to-maturity positions' also depend on migration risk. Independently from the fact that 'true' negotiations occur, a periodic assessment of credit quality is required and, if

**TABLE 3-1** A Classification of Credit Risk

| Correlation with financial risks | Risks | Valuation | |
|---|---|---|---|
| Low ↑ | • Default risk<br>• Recovery risk<br>• Exposure risk | Defualt-mode valuation | Marked-to-market valuation |
| ↓ High | • Migration risk<br>• Spread risk<br>• Liquidity risk | Value-based valuation | |
| *Pure financial risks (interest rate risk, exchange rate risk, inflation risk)* | | | |

meaningful changes in credit quality arise, credit provisions have consequently to be arranged, and both losses and gains have to be recorded.

Finally, if positions exposed to credit risk are included in the trading book and valued at market prices, a new source of risk arises. In fact, even in the case of no rating migrations, investors may require different risk premiums due to different market conditions, devaluating or revaluating existing exposure values accordingly. This is the spread risk, and it generates losses and gains as well.

The recent financial crisis has underlined an additional risk (asset liquidity risk) related to the possibility that the market becomes less liquid and that credit exposures have to be sold, accepting lower values than expected (Finger, 2009a).

Credit ratings are critical tools for analyzing and measuring almost all these risk concepts. Consider for instance that risk premiums are usually rating sensitive, as well as market liquidity conditions.

### Default Risk

Without a counterparty's credit quality measure, in particular a default probability, we cannot pursue any modern credit risk management approach. The determination of this probability could be achieved through the following alternatives:

- The observation of historical default frequencies of borrowers' homogeneous classes. The borrowers' allocation to different credit quality classes has traditionally been based on subjective analysis, leveraging on analytic competences of skilled credit officers. Rating agencies have an almost secular track record of assigned ratings and default rates observed *ex post* per rating class.
- The use of mathematical and statistical tools, based on large databases. The bank's credit portfolios, which have thousands of positions observed in their historical behavior, allow the application of statistical methods. Models combine various types of information in a score that facilitates the borrowers' assignment to different risk classes. The same models permit a detailed *ex ante* measure of expected probability and facilitate monitoring over time.
- The combination of both judgmental and mechanical approaches (hybrid methods). Automatic classification

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is generated by statistical or numerical systems. Experts correct results by integrating qualitative aspects, in order to reach a classification that combines both potentialities (i.e., the systematic statistical analysis, expert competence and their ability to deal with soft information). Even in this case, the historical observation, combined with statistical methods, permits a default probability associated to each rating class to be reached.

- A completely different approach 'extracts' the implicit probability of default embedded in market prices (securities and stocks). The method can obviously only be applied to public listed counterparties on equity or securities markets.

The measure of default risk is the 'probability of default' within a specified time horizon, which is generally one year. However, it is also important to assess the cumulative probabilities when exposure extends beyond one year. The probability may be lower when considering shorter time horizons, but it never disappears. In overnight lending, too, we have a non-zero probability, given that sudden adverse events or 'hidden' situations to analysts may occur.

## Recovery Risk

The recovery rate is the complement to one of 'the loss in the event of default' (typically defined as LGD, Loss Given Default, expressed as a percentage). Note that here default is 'given', that is to say that it has already occurred.

In the event of default, the net position proceeds dependent on a series of elements. First of all, recovery procedures may be different according to the type of credit contracts involved in the legal system and the court that has jurisdiction. The recovery rate also depends on the general economic conditions: results are better in periods of economic expansion. Defaulted borrowers' business sectors are important because assets values may be more or less volatile in different sectors. Also, covenants are important; these agreements between borrower and lender raise limits to borrower's actions, in order to provide some privileges to creditors. Some covenants, such as those limiting the disposal of important assets by the borrower, should be considered in LGD estimation. Other types of collateral may reduce the probability of default rather than the LGD; these are delicate aspects to models (Altman, Resti and Sironi, 2005; Moody's Investor Service, 2007).

*Ex ante* assessment of recovery rate (and corresponding loss given default) is by no means less complex than assessing the probability of default. Recovery rate data are much more difficult to collect, due to many reasons. Recoveries are often managed globally at the counterparty's position and, as a consequence, their reference to the original contracts, collaterals, and guarantees is often lost. Default files are mainly organized to comply with legal requirements, thus losing uniformity and comparability over time and across positions. Even when using the most sophisticated statistical techniques it is very difficult to build comprehensive models. Then, less sophisticated procedures are applied to these assessments, often adopting 'top down' procedures, which summarize the average LGD rates for a homogeneous set of facilities and guarantees. 'Loss given default ratings' (also known as 'severity ratings') are tools used to analyze and measure this risk.

## Exposure Risk

Exposure risk is defined as the amount of risk in the event of default. This amount is quite easily determined for term loans with a contractual reimbursement plan. The case of revolving credit lines whose balance depends more on external events and borrower's behavior is more complex. In this case, the due amount at default is typically calculated using model's specification, such as the following:

$$\text{Exposure at default} = \text{drawn} + (\text{limit} - \text{drawn})^{*}\ \text{LEQ}$$

where:

- drawn is the amount currently used (it can be zero in case of back-up lines, letters of credit, performance bonds or similar),
- limit is the maximum amount granted by the bank to the borrower for this credit facility,
- LEQ (Loan Equivalency Factor) is the rate of usage of the available limit, beyond the ordinary usage, in near-to-default situations.

In other cases, such as account receivables' financing, additional complexities originate from commercial events of non-compliance in contractual terms and conditions that can alter the amounts which are due from the buyer (the final debtor) to the bank. For derivative contracts, the due value in the event of default depends on market conditions of the underlying asset. The Exposure at Default (EAD) may therefore assume a probabilistic nature: its amount is a forecast of future events with an intrinsically



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stochastic approach. EAD models are the tools used to measure EAD risk.

## KEY CONCEPTS

### Expected Losses

A key concept of credit risk measurement is 'expected loss': it is the average loss generated in the long run by a group of credit facilities. The 'expected loss rate' is expressed as a percentage of the exposure at default.

The approach to determine expected loss may be financial or actuarial. In the former case, the loss is defined in terms of a decrease in market values resulting from any of the six credit risks listed in Table 3-1. In the latter case, the last three risks indicated in Table 3-1 (migration risk, spread risk, and liquidity risk) are not taken into consideration, only losses derived from the event of default are considered (therefore, it is generally known as 'default mode approach').

For banks, the expected loss is a sort of industrial cost that the lender has to face sooner or later. This cost is comparable to an insurance premium invested in mathematical risk-free reserves to cover losses over time (losses that actually fluctuate in different economic cycle phases).

Expected loss on a given time horizon is calculated by multiplying the following factors:

- probability of default
- severity of loss (LGD rate)
- exposure at default.

The expected loss rate, in percentage of EAD, only multiplies the first two measures.

### Unexpected Losses, VaR, and Concentration Risk

As the wording itself suggests, expected loss is expected (at least in the long term) and, therefore, it is a cost that is embedded into bank business and credit decisions. It is a sort of industrial cost of bank business. In short time horizons, banks' expected losses may strongly deviate from the long-term average due to credit cycles and other events. Therefore, the most important risk lies in the fact that actual losses may deviate from expectations and, in particular, may become much higher than expected. In this case, the bank's capability to survive as a going concern is at stake. In short, the true concept of risk lies in unexpected loss rather than in expected loss.

Banks face unexpected losses by holding enough equity capital to absorb losses that are recorded in the income statement during bad times. Capital is replenished in good times by higher-than-expected profits. In credit risk management, capital has the fundamental role of absorbing unexpected losses and thus has to be commensurate with estimates of the loss variability over time.

In general, banks should hold enough capital to cover all risks, and not just credit risk. Bank managers must ensure they have an integrated view of risks in order to identify the appropriate level of capitalization. Calculating capital needs is only possible by using robust analytical risk models and measures. Credit risk measures are essential to contribute to a proper representation of risk.

From this perspective, ratings are key measures in determining credit contributions to the bank's overall risk. In fact, loss variability is very different for exposures in different rating classes. Therefore, on one hand, ratings directly produce measures of expected default rates and of expected loss given default, which impact credit provisions (costs written in banks' income statements). On the other hand, these measures help to differentiate exposures in terms of variability of default and LGD measures and their impact on banks' capital needs.

In many fields, unexpected losses are usually measured by standard deviation. However, in the case of credit risk, standard deviation is not an adequate measure of risk because the distribution (of losses, of default rates, and losses given default) is not symmetric (Figure 3-1).

In the case of credit risk, a better measure of variability is VaR (value at risk, here as a percentage of EAD), defined as the difference between the maximum loss rate at a certain confidence level and the expected loss rate, in a given time horizon. This measure of risk also indicates the amount of capital needed to protect the bank from failure at the stated level of confidence. This amount of capital is also known as 'economic capital'.

For instance, Figure 3-1 shows the maximum loss the portfolio might incur with a confidence level of cl% (say 99%, which means considering the worst loss rate in 99% of cases), the expected loss, and the value at risk. VaR



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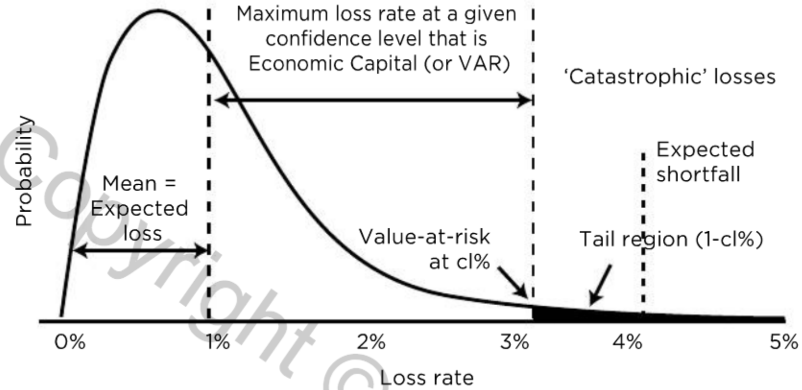


**FIGURE 3-1** Loss rate distribution and economic capital.

defines the capital that must be put aside to overcome unexpected losses in 99% of the cases; the bank's insolvency is, therefore, confined to catastrophic loss rates whose probabilities are no more than one percent (1-cl%).[1]

In the case of credit risk, probability distributions are, by their nature, highly asymmetric. Adverse events may have a small probability but may impact significantly on banks' profit and loss accounts. The calculation of economic capital requires the identification of a probability density function. 'A credit risk model encompasses all of the policies, procedures and practices used by a bank in estimating a credit portfolio's probability density function' (Basel Committee, 1999a). In order to draw a loss (or default, LGD, EAD) distribution and calculate VaR measures, it is possible to adopt a parametric closed-form distribution, to use numerical simulations (such as Monte Carlo) or to use discrete probability solutions such as setting scenarios.

Up to now, expected losses and VaR measures (which are more specifically known as 'stand alone VaR') offer important summary measures of risk, but they do not take into account the risk deriving from portfolio concentration. The problem is that the sum of individual risks does not equal the portfolio risk. Increasing the number of loans in a portfolio and their diversification (in terms of borrowers, business sectors, regions, sizes and market segments, production technologies and so forth) reduces portfolio risk because of the less than perfect correlation among different exposures.

For this reason, a seventh risk concept should be added to Table 3-1 when considering the portfolio perspective: concentration risk. It arises in a credit portfolio where borrowers are exposed to common risk factors, that is, external conditions (interest rates, currencies, technological shifts and so forth). These risk factors may simultaneously impact on the willingness and ability to repay outstanding debts of a large number of counterparties. If the credit portfolio is specifically exposed to certain risk factors, the portfolio is 'concentrated' in respect to some external adverse events.

Traditionally, to avoid this risk, banks split claims on a large number of borrowers, limiting exposures and excessive market shares on individual customers. The idea was: the higher the portfolio granularity, the less risky the portfolio. In a context of quantitative credit risk management, the granularity criterion is integrated (and sometimes replaced) by the correlation analysis of events of default and of changes in credit exposures values.

'Full portfolio credit risk models' describe these diversification effects giving a measure of how much concentration is provided by the individual borrowers' risk factors; they also allow managing the credit portfolio risk profile as a whole or by segments. Without a credit portfolio model, it is not possible to analytically quantify the marginal risk attributable to different credit exposures, either if they are already underwritten or if they are just submitted for approval. Only if a portfolio model is available, is it then possible to estimate the concentration risk brought to the bank by each counterparty, transaction, facility type, market or commercial area. It is crucial to calculate default co-dependencies, that is to say, the possibility that more counterparts in the same risk scenario can jointly default or worsen their ratings.

There are two basic approaches to model default co-dependencies. The former is based on 'asset value correlation' and the framework proposed by Merton (1974): the effect of diversification lies in the possibility that the counterparties' value is influenced by external economic events. The event of joint default is related to the probability that two borrowers' assets values fall below their respective outstanding debt. The degree of diversification

[1] The recent financial crisis has shown the opportunity to have measures on what may happen beyond the VaR threshold, in order to integrate VaR. Therefore, 'expected shortfall' is gaining consideration among risk managers; analytically, it is (in percentage) the average loss rate that is expected beyond a certain threshold defined in terms of confidence level.

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could therefore be measured by the correlation among assets' values and by considering the outstanding debts of the two borrowers. The latter is based on a direct measure of the 'default correlation' in historical correlations of data of homogenous groups of borrowers (determined by elements such as business sector, size, geographical area of operation and so forth).

According to Markowitz's fundamental principle, only if the correlation coefficient is one is the portfolio risk equal to the sum of the individual borrowers' risks. On the contrary, as long as default events are not perfectly positively correlated, the bank will have to separately deal in different financial periods with its potential losses. Therefore, the bank can face the risk in a more orderly manner, with less intense fluctuations in provisioning and smaller committed bank capital.

In this perspective, it is also important to measure how individual exposures contribute to concentration risk, to the overall portfolio risk, and to the portfolio's economic capital. A 'marginal VaR' measure, indicating the additional credit portfolio risk implied by an individual exposure, is needed.

By defining:

- $UL_{portfolio}$ as the portfolio unexpected loss
- $w_i$ as the weight of the $i^{th}$ loan on the overall portfolio
  $\rho_{i;portfolio}$ as the default correlation between the $i^{th}$ loan and overall portfolio
- $ULC_i$ as the marginal contribution of the $i^{th}$ loan portfolio unexpected loss.

this marginal contribution can be expressed as:

$$ULC_i = \frac{\partial UL_{portfolio}}{\partial_{w_i}} w_i$$

and in a traditional variance/covariance approach:

$$ULC_i = \rho_{i;portfolio}\, w_i\, UL_{portfolio}$$

$ULC_i$ can be used in many useful calculations. For instance, a meaningful measure is given by the $i^{th}$ loan 'beta', defined as:

$$\beta_i = \frac{ULC_i/w_i}{UL_{portfolio}}$$

This measure compares the marginal $i^{th}$ loan risk with the average risk at portfolio level. If $\beta$ is larger than one, then the marginal risk adds more than the average risk to the portfolio; the reverse is true if $\beta$ is lower than one. In this way, loans can be selected using betas, and thus it is possibly to immediately identify transactions that add concentration to the portfolio (i.e., they have a beta larger than one) and others that provide diversification benefits (beta smaller than one).

At different levels of the portfolio (individual loan, individual counterparty, counterparties' segments, sectors, markets and so forth), correlation coefficients ($\rho_{i;portfolio}$) and $\beta_i$ can be calculated, achieving a quantitative measure of risk drivers. These measures can offer crucial information to set lending guidelines and to support credit relationship management. A number of publications, such as Resti and Sironi (2007) and De Servigny and Renault (2004), cover this content in more depth.

## Risk Adjusted Pricing

Capital is costly because of shareholders' expectations on return on investment. Higher VaRs indicate the need for higher economic capital; in turn, this implies the need for higher profits. Cost of capital multiplied by VaR is a lending cost, which has to be incorporated into credit spreads (if the bank is price setter) or considered as a cost (if the bank is price taker) in order to calculate risk adjusted performance measures. Lending decisions are as relevant for banks as investment decisions are for industrial companies; setting lending policies is as important to banks as selecting technology and business models for industrial companies.

The availability of information such as expected and unexpected losses can substantially innovate the way credit strategies are set. Today, the relevance of economic capital for pricing purposes is widely recognized (Saita, 2007). These measures must be incorporated into loan pricing. In theory, under the assumption of competitive financial markets, prices are exogenous to banks, which act as price takers and assess a deals expected return *(ex ante)* and actual return *(ex post)* by means of risk adjusted performance measures, such as the risk adjusted return on capital.

However, in practice, markets are segmented. For example, the loan market can be viewed as a mix of wholesale segments, where banks tend to behave more as price takers, and retail segments where, due to well known market imperfections (information asymmetries, monitoring costs and so forth), banks tend to set prices for their customers.



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In both cases, price may become a tool for credit policies and a way to shape the credit portfolio risk profile (in the medium term) by determining rules on how to combine risk and return of individual loans.

Therefore, the pricing policy drives loan underwriting and may incentivize cross-selling and customers' relationships management. At the bank's level, a risk-based pricing policy:

- structures the basis for active portfolio risk management (e.g., using credit derivatives);
- integrates credit risks with market risks and operational risks, supporting an effective economic capital budgeting;
- helps to formulate management objectives in terms of economic capital profitability at business units' level.

Many banks use risk adjusted performance measures to support pricing models; the most renowned is known as RAROC (risk adjusted return on capital) and has many variants, such as RARORAC (risk adjusted return on risk adjusted capital). In the late 1970s, the concept of RAROC was introduced for the first time by Bankers Trust. This approach has become an integral part of the investment banks' valuations since the late 1980s (after the 1987 market crash and the 1991 credit crisis). Gradually, applications moved from management control (mainly at divisional level) to front line activities, in order to assess individual transactions. Since the mid 1990s, most of the major international transactions have been subject to prior verification of 'risk adjusted return' before loan marketing and underwriting.

The rationale of these applications is given by the theory of finance. The main assumption is that, ultimately, the value of different business lines depends on the ability to generate returns higher than those needed to reward the market risk premium required by capital which is absorbed to face risk. The Capital Asset Pricing Model (CAPM) provides a basis for defining the terms of the risk-return pattern. Broadly speaking and unless there are short-term deviations, credit must lie on the market risk/return line, taking into consideration correlation with other asset classes.

The credit spread has to be in proportion with the market risk premium, taking into consideration the risk premium of comparable investments. Otherwise (within the banking group or among different banks) market forces tend to align risk adjusted capital returns to the intrinsic value of underlying portfolios.

In particular, it is possible to fix the target return for the bank's credit risk-taking activities beyond the threshold of cost of capital. The best known practice is to establish a target level, for example, in terms of target Return on Equity (ROE; an accounting expression of the cost of equity) applied to the assets assigned to the division. The condition for value creation by a transaction is, therefore:

$$\text{RARORAC} > \text{ROE}_{\text{target}}$$

This relationship can also be expressed in terms of EVA (Economic Value Added):

$$\text{EVA} = (\text{RARORAC} - K_e) \times \text{Economic Capital}$$

in which $K_e$ is the cost of shareholders' capital.

Risk-based pricing typically incorporates fundamental variables of a value-based management approach. For example, the pricing of credit products will include the cost of funding (such as an internal transfer rate on funds), the expected loss (in order to cover loan loss provisions), the allocated economic capital, and extra return (with respect to the cost of funding) as required by shareholders. Economic capital influences the credit process through the calculation of a (minimum) interest rate that is able to increase (or, at least, not decrease) shareholders' value. A simplified formula can be expressed as:

$$RARORAC = \frac{\text{Spread + Fees – Expected loss – Cost of capital} \\ \text{– Cost of operations}}{\text{Economic capital}}$$

Depending on the product and the internal rules governing the credit process, decisions regarding prices can sometimes be overridden. For example, this situation could occur when considering the overall profitability of a specific customer's relationship or its desirability (due to reputational side effects stemming from the customer relationship, even if it proves to be no longer economically profitable). Generally, these exceptions to the rule are strictly monitored and require the decision to be taken by a higher level of management.

Regardless of the role played by banks as price taker or price maker institutions, the process cannot be considered complete until feedback about the final outcome of the taken decision has been provided to management. The measurement of performance can be extended down to the customer level, through the analysis of customer



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profitability. Such an analysis aims to provide a broad and comprehensive view of all the costs, revenues, and risks (and, consequently, required economic capital) generated by each customer.

While implementation ·of this kind of analysis involves complex issues related to the aggregation of risks at the customer level, its use is evident in identifying unprofitable or marginally profitable customers who use resources (and above all capital) that could be allocated more efficiently to more profitable relationships.

This task is generally accomplished by segmenting customers in terms of ranges of (net) return per unit of risk. Provided the underlying inputs have been properly measured and allocated (not a simple task as it concerns risks and, even more, costs), this technique provides a straightforward indication of areas for intervention in managing customer profitability.

By providing evidence on the relative risk adjusted profitability of customer relationships (as well as products), economic capital can be used in optimizing the risk-return trade-off in bank portfolios. Recently, the adoption of these models has been accelerated because:

- investors are more sophisticated and promote the adoption of specific tools to maximize shareholders' value;
- banking groups are becoming large, complex, multinational conglomerates, and are more and more organized by distinct profit centers (business units). This implies an internal 'near-market' competition for resources and capital allocation. This organizational pattern requires risk adjusted performance measures and goals assigned throughout the whole structure.

In this context, ratings become not only a useful tool but also a necessary tool. In fact, without borrowers' creditworthiness measures, it is not possible to:

- operate on capital markets;
- manage the critical forces underlying value creation;
- compare the economic performance of business units or divisions and coordinate their actions.

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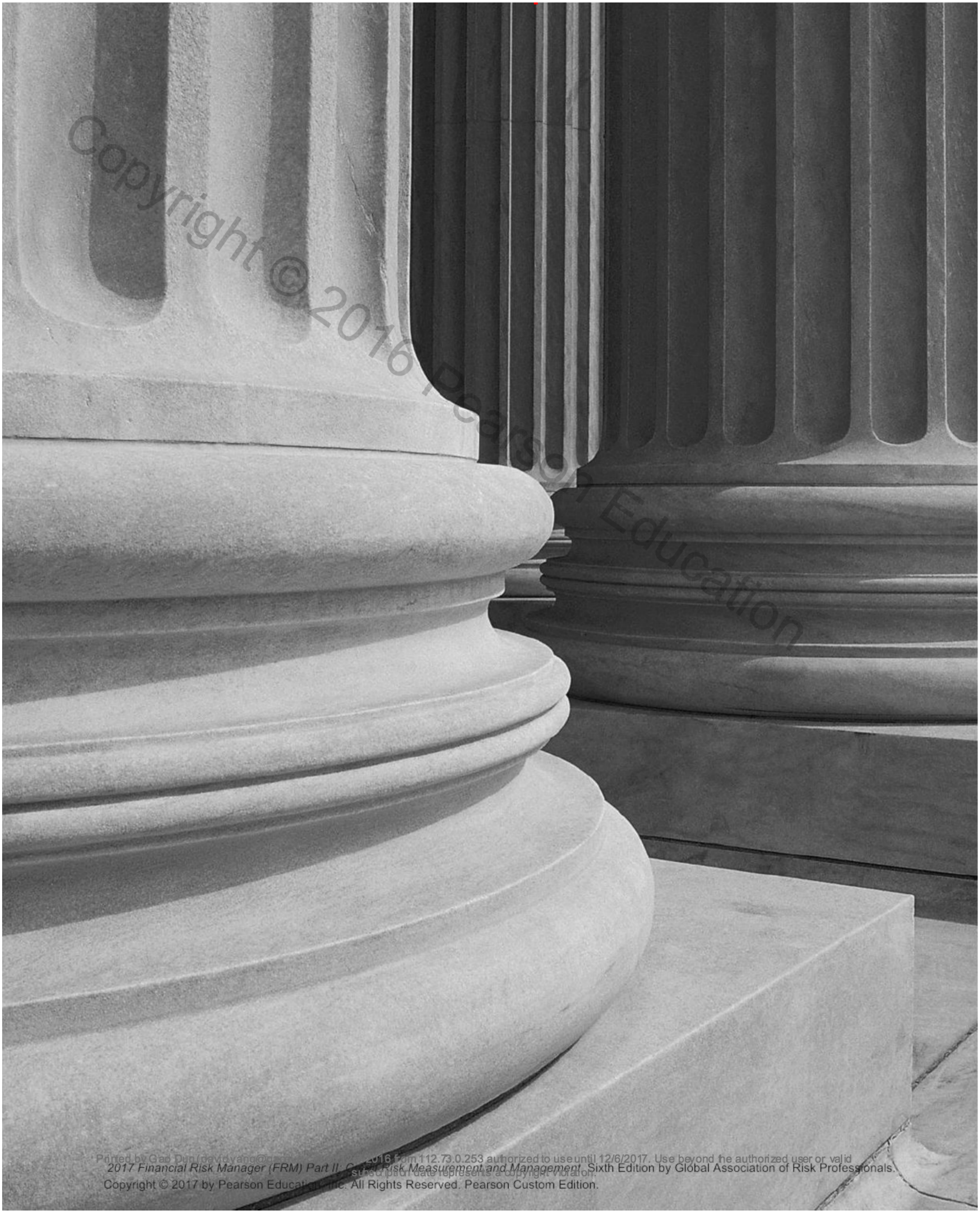

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# Rating Assignment Methodologies

# 4

## Learning Objectives

After completing this reading you should be able to:

- Explain the key features of a good rating system.
- Describe the experts-based approaches, statistical-based models, and numerical approaches to predicting default.
- Describe a rating migration matrix and calculate the probability of default, cumulative probability of default, marginal probability of default, and annualized default rate.
- Describe rating agencies' assignment methodologies for issue and issuer ratings.
- Describe the relationship between borrower rating and probability of default.
- Compare agencies' ratings to internal experts-based rating systems.
- Distinguish between the structural approaches and the reduced-form approaches to predicting default.
- Apply the Merton model to calculate default probability and the distance to default and describe the limitations of using the Merton model.
- Describe linear discriminant analysis (LDA), define the Z-score and its usage, and apply LDA to classify a sample of firms by credit quality.
- Describe the application of a logistic regression model to estimate default probability.
- Define and interpret cluster analysis and principal component analysis.
- Describe the use of a cash flow simulation model in assigning rating and default probability, and explain the limitations of the model.
- Describe the application of heuristic approaches, numeric approaches, and artificial neural networks in modeling default risk and define their strengths and weaknesses.
- Describe the role and management of qualitative information in assessing probability of default.

*Excerpt is Chapter 3 of* Developing, Validating and Using Internal Ratings: Methodologies and Case Studies, *by Giacomo De Laurentis, Renato Maino and Luca Molteni.*

*See bibliography on pp. 515–518.*



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## INTRODUCTION

In Chapter 3, the central role of ratings in supporting the new credit risk management architecture was emphasized. This role can be illustrated as an upside-down pyramid, with borrower's rating at its foundation (Figure 4-1). The event of default is one of the most significant source of losses in a bank's profit and loss statement and assumes a central position in internal governance systems as well as in the eyes of specific supervisors' and monetary policy authorities' scrutiny.

Moreover, rating supports credit pricing and capital provisions to cover unexpected credit losses. These essential elements are at the foundation of many business decision making processes, touching all the organizational and operational aspects, up to business model selection, services offering, incentives and compensation systems, capital adequacy, internal controls systems, and internal checks and balances along the value chain of credit risk underwriting, management, and control.

Subsequently, the complex and delicate functions mentioned above pose relevant charges to rating assignment, far beyond only the technical requirement, even if it is considered a highly specialist component. Examined in the following chapters is how to calculate default probabilities through an appropriate rating system putting together coherent organizational processes, models, quantitative tools, and qualitative analyses.

Rating is an ordinal measure of the probability of the default event on a given time horizon, having the specific features of measurability, objectivity, and homogeneity, to properly confront counterparts and segments of the credit portfolio. Rating is the most important instrument that differentiates traditional from modern and quantitative credit risk management. The whole set of applications mentioned before, which concerned expected losses, provisions, capital at risk, capital adequacy, risk adjusted performance measurement, credit pricing and control, and so forth, are essentially based on reliable probability measures.

Probabilities are expectations. If our *ex ante* assessment is accurate enough, over time, probabilities become actual observed frequencies, at least in pre-defined confidence intervals. This property implies that a specific organizational unit has to periodically verify any deviation out of confidence intervals, assessing impacts and effects, validating the assumptions and models that generated the *ex ante* expectations.

The rating assessment backs up an important, well structured internal governance system, supporting

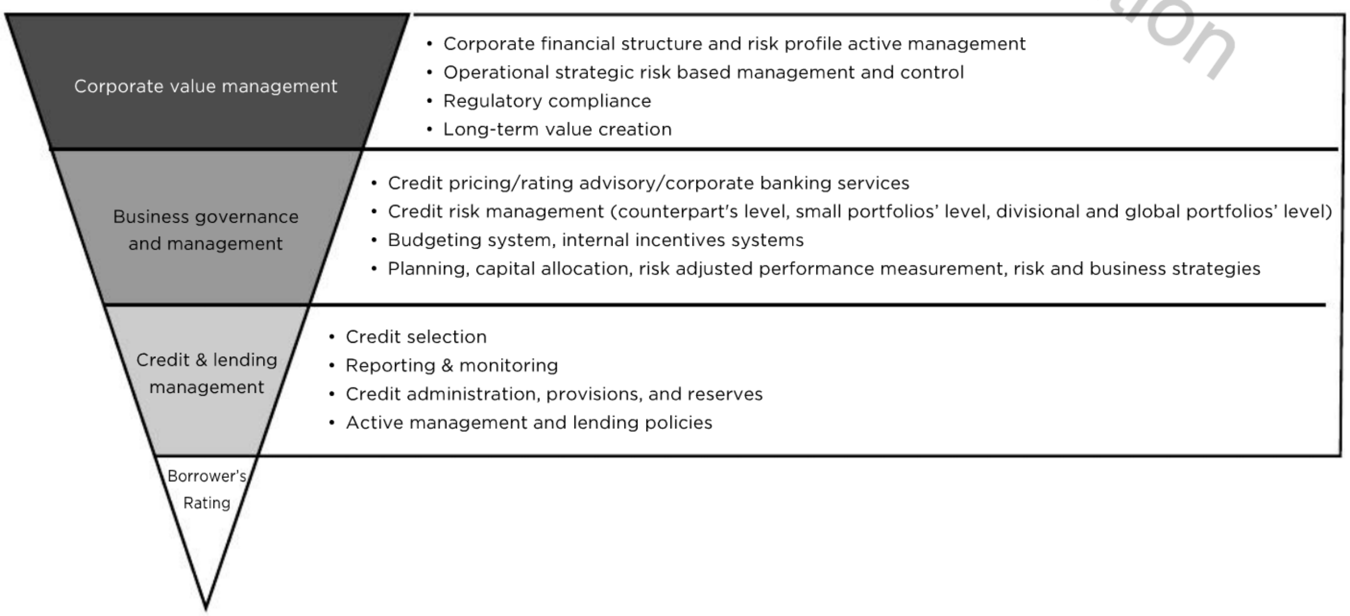


**FIGURE 4-1** Credit governance system and borrower's rating.



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decisions at the organization's different layers. This is why internal rating has to be as 'objective' as possible, in the sense that different teams of analysts—who are tackling the same circumstances, with the same level of information, applying the same methodology, in the same system of rules and procedures—have to arrive at a similar rating, accepting only minor misalignments. This is the only way to make decisions on a homogeneous, reliable and verifiable basis, maintaining full accountability over time.

Inevitably, there will be room for discretion, entrepreneurialism and subjectivity but a sound basis has to be provided to the whole process and control. This will not happen, obviously, if ratings were the result of individual and subjective analysis, contingently influenced by the point-in-time business environment or from highly personal competences that could be different each time, from one analyst to another.

These considerations do not imply that the credit analyst has to be substituted by tight procedures that stifle competences and professionalism. On the contrary, procedures have to put strong pressure on accountability and professionalism when needed to reach a better final decision. At the same time, it is necessary to avoid a sort of lenders' irresponsibility to fully take into account borrower's individual projects, initiatives, needs, and financial choices. In addition, lending decisions are not right or wrong; ratings only indicate that some choices are riskier than others, because a bank is responsible toward bondholders, depositors, and customers.

Therefore, rating systems have three desirable features in terms of measurability and verifiability, objectivity and homogeneity, and specificity:

- Measurability and verifiability: these mean that ratings have to give correct expectations in terms of default probabilities, adequately and continuously back tested.
- Objectivity and homogeneity: the former means that the rating system generates judgments only based on credit risk considerations, while avoiding any influence by other considerations; the latter means that ratings are comparable among portfolios, market segments, and customer types.
- Specificity: this means that the rating system is measuring the distance from the default event without any regards to other corporate financial features not directly related to it, such as short term fluctuations in stock prices.

These three features help to define a measure of appropriateness of internal rating systems and are decisive in depicting their distinctive suitability for credit management. However, the ability of different methodologies and approaches to deal with these desirable profiles is a matter of specific judgment, given the tradeoffs existing among them.

Here, the following are distinguished and separately analyzed:

1. experts-based approaches
2. statistical-based models
3. heuristic and numerical approaches.

## EXPERTS-BASED APPROACHES

### Structured Experts-Based Systems

Defaults are relatively rare events. Even in deeper recessions a default rate of around 2–5% is observed and each default appears like a highly individual story in approaching default, in recovery results, and in final outcome. A credit analyst (regardless of whether in a commercial bank or in an official rating agency) is, above all, an experienced person who is able to weigh intuitions and perceptions through the extensive knowledge accumulated in a long, devoted, and specialist career.

Also, economic theory regarding the framework of optimal corporate financial structure required a long development time, due to:

- lack of deep, homogenous, and reliable figures
- dominance of business and industrial competition problems rather than financial ones.

It is necessary to look back to the 1950s to see the first conceptual patterns on corporate financial matters, culminating with the Modigliani-Miller framework to corporate value and to the relevance of the financial structure. In the 1960s, starting from preliminary improvements in corporate finance stemming from Beaver (1966), the discipline became an independent, outstanding topic with an exponential amount of new research, knowledge, and empirical results. It is also necessary to have to recall the influential insight of Wilcox (1971), who applied 'gambler's



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ruin theory' to business failures using accounting data. Shortly after, from this perspective, the corporate financial problem was seen as a risky attempt to run the business by 'betting' the company's capital endowment. At the end of each round of betting, there would be a net cash in or net cash out. The 'company game' would end once the cash had finished. In formal terms, Wilcox proposed the relationship between:

- the probability of default ($P_{default}$),
- the probability of gains, *m,* and of losses (1 − *m);* the constraint is that profits and losses must have the same magnitude,
- the company initial capital endowment, CN,
- the profit, U, for each round of the business game, in the form of

$$P_{default} = \left(\frac{1-m}{m}\right)^{\frac{CN}{U}}$$

CN/U is the inverse of the return on equity ratio (ROE) and, in this approach, it is also the 'company's potential survival time'. Given the probability, *m,* then the process could be described in stochastic terms, identifying the range in which the company survival is assured or is going to experience the 'gambler's ruin'.

Many practical limitations impeded the model and, therefore, it could not be applied in practice, confining it to a theoretical level. Nevertheless, the contribution was influential in the sense that:

- for the first time, an intrinsically probabilistic approach was applied to the corporate default description;
- the default event is embedded in the model, is not exogenously given, and stems from the company profile (profitability, capital, business turbulence and volatility);
- the explanatory variables are financial ones, linked with the business risk through the probability, *m;*
- there is the first definition of the 'time to default' concept, that has been used since the 1980s in the Poisson-Cox approach to credit risk.

These model features are very similar to Merton's model, which was proposed some years later; Merton's model is widely used today and is one of the most important innovations in credit risk management.

Another contribution that is worth mentioning is the 'point of no return theory,' an expression that is common to war strategy or air navigation. The 'no return point' is the threshold beyond which one must continue on the current course of action, either because turning back is physically impossible or because, in doing so, it would be prohibitively expensive or dangerous. The theory is important because it has been defined using an intrinsically dynamic approach (Brunetti, Coda, and Favotto, 1984). The application to financial matters follows a very simple idea: the debt generates cash needs for interest payments and for the principal repayment at maturity. Cash is generated by the production, that is, by business and operations. If the production process is not generating enough cash, the company becomes insolvent. In mathematical terms this condition is defined as:

$$\frac{\partial EBIT}{\partial T} \geq \left(\frac{\partial(OF + \Delta D)}{\partial T}\right)$$

that is to say, the company will survive if the operational flow of funds (industrial margin plus net investments or divestments) is no less than interest charges and principal repayment, otherwise new debt is accumulated and the company is destined to fail. The balance between debt service and flow of funds from operations is consequently critical to achieve corporate financial sustainability over time. Therefore, the 'no return point' discriminates between sustainability and the potential path to default.

This idea plays an important role in credit quality analysis. Production, flow of funds, margins, and investments have to find a balance against financial costs; the default probability is, in some way, influenced by the 'safe margin', intended as the available cushion between operational cash generation and financial cash absorption. The company financial soundness is a function of the safe margins that the company is able to offer to lenders, like surpluses against failure to pay in sudden adverse conditions. It is an idea that is at the root of many frameworks of credit analysis, such as those used by rating agencies, and is at the basis of more structured approaches derived from Merton's option theory applied to corporate financial debt.

Credit quality analysis is historically concentrated on some sort of classification, with an aim to differentiate borrowers' default risk. Over time, the various tools changed from being mainly qualitative-based to being more quantitative-based. In the more structured



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approaches, the final judgment comes from a system of weights and indicators. Mostly, applied frameworks have symbolic acronyms such as:

- Four Cs: Character—Capital—Coverage—Collateral (proposed by Altman of New York University in various editions till the end of the 1990s).
- CAMELS: Capital adequacy—Asset quality—Management—Earnings—Liquidity—Sensitivity (J.P. Morgan approach).
- LAPS: Liquidity—Activity—Profitability—Structure (Goldman Sachs valuation system).

The final result is a class, that is, a discrete rank, not a probability. To reach a probability, an historical analysis has to be carried out, counting actual default frequencies observed per class over time.

During the 1980s and 1990s, industrial economics was deeply influenced by the competitive approach, proposed mainly by Porter (1980, 1985): economic phenomena, like innovation and globalization, deeply changed traditional financial analysis, creating the need to devote attention to the competitors' qualitative aspects, such as trading power, market position, and competitive advantages. These aspects had to be integrated with traditional quantitative aspects such as demand, costs, resources, and trading flows. Consequently, in the final judgment, it is critical to identify coherence, consistency, and appropriateness of the company's business conduct in relation to the business environment and competition.

Porter's important point is that qualitative features are as relevant as the financial structure and production capacity. Porter's publications can be considered today as at the roots of qualitative questionnaires and surveys that usually integrate the rating judgment, giving them solid theoretical grounds and conceptual references.

## Agencies' Ratings

The most relevant example of structured analysis applications is given by rating agencies (Ganguin and Bilardello, 2005). Their aim is to run a systematic survey on all determinants of default risk. There are a number of national and international rating agencies operating in all developed countries (Basel Committee, 2000b). The rating agencies' approach is very interesting because model-based and judgmental-based analyses are integrated (Adelson and Goldberg, 2009). They have the possibility to surmount the information asymmetry problem through a direct expert valuation, supported by information not accessible to other external valuators. Rating agencies' revenues derive for the most part by counterpart's fees; only a small amount is derived from the direct selling of economic information to investors and market participants. This business model is apparently very peculiar because of the obvious conflict of interests between the two parties. If the cost of the rating assignment is charged to companies that have the most benefit from it, how is it possible to be sure that this judgment will be reliable enough? Nevertheless, this business model is founded on a solid basis, as Nobel Laureate George Ackerloff and the 'lemon principle' can help us to understand. If there is a collective conviction among market participants that exchanged goods were of bad quality, the seller of better quality goods will encounter many difficulties in selling them, because they will have trouble in convincing people of the quality of his offer. In such circumstances, the seller of better quality goods:

- either tries to adapt, and switch to low quality goods in order to be aligned with the market judgment,
- or has to find a third party, a highly reputable expert, that could try to convince market participants that the offer is of really good quality and it is worth a higher price.

In the first case, the market will experience a suboptimal situation, because part of the potential offer (good quality products) will not be traded. In the second case, the market will benefit from the reliable external judgment, because of the opportunity to segment demand and to gain a wider number of negotiated goods.

Generally speaking, when there is information asymmetry among market participants (i.e., inability for market participants to have a complete and transparent evaluation of the quality of goods offered) only high reputation external appraisers can assure the quality of goods, overcoming the 'lemon' problem. Traders, investors, and buyers can lever on the expert judgment. Therefore, issuers are interested in demonstrating the credit quality of their issues, and rating agencies are interested in maintaining their reputation. The disruption in the evaluator's reputation is something that could induce a much wider market disruption (this observation is very important in light of the recent financial crisis, where rating agencies'



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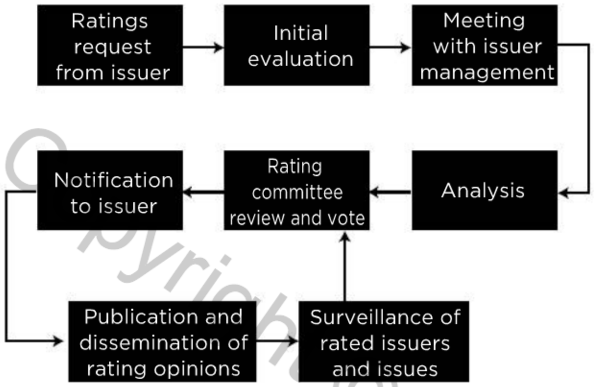


**FIGURE 4-2** Decision making process for rating assignment at Standard & Poor's.

*Source:* Standard & Poor's (2009c).

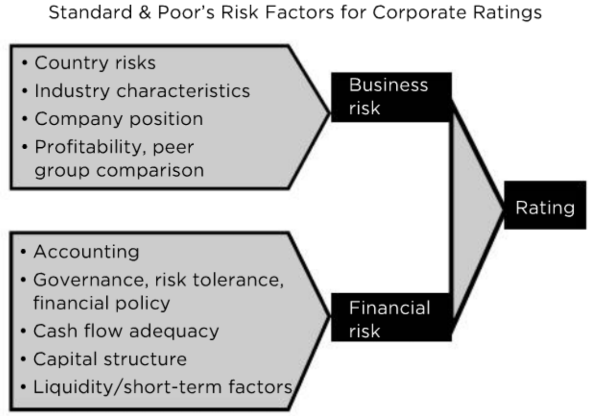


**FIGURE 4-3** Analytical areas for rating assignment at Standard & Poor's.

*Source:* Standard & Poor's (2008).

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structured-products judgments have been strongly criticized).

Consequently, the possibility to obtain privileged information of the counterparty's management visions, strategies, and budgeting is essential to a reliable rating agencies' business model; as a result, the structure of the rating process becomes a key part of the rating assignment process because it determines the possibility to have independent, objective, and sufficient insider information. Standard & Poor's (S&P) rating agency scheme is illustrated in Figure 4-2.

Rating agencies' assignment methodologies are differentiated according to the counterparty's nature (corporations, countries, public entities and so forth) and/or according to the nature of products (structured finance, bonds and so forth). Here attention is concentrated on corporate borrowers. The final rating comes from two analytical areas (Figure 4-3): business risks and financial risks. This follows the fundamental distinction proposed by Modigliani and Miller in the 1950s.

The main financial ratios used by the Standard & Poor's rating agency are:

- profitability ratios from historical and projected operations, gross and net of taxes;
- coverage ratios such as cash flow from operations divided by interest and principal to be paid;
- quick and current liquidity ratios.

Generally speaking, the larger the cash flow margins from operations, the safer the financial structure; and, therefore, the better the borrower's credit rating. This general rule is integrated with considerations regarding the country of incorporation and/or of operations (so called 'sovereign' risk), the industry profile and the competitive environment, and the business sector (economic cycle sensitivity, profit and cash flow volatility, demand sustainability and so forth).

Other traditional analytical areas are: management's reputation, reliability, experience, and past performance; coherence and consistency in the firm's strategy; organization adequacy to competitive needs; diversifications in profit and cash flow sources; firm's resilience to business volatility and uncertainty. Recently, new analytical areas were introduced to take new sources of risk into account. The new analytical areas are as follows:

- internal governance quality (competence and integrity of board members and management, distribution and concentration of internal decision powers and layers, succession plans in case of critical management resources' resignation or vacation and so forth);
- environmental risks, technology and production processes compliance and sustainability;
- potential exposure to legal or institutional risks, and to main political events;
- potential hidden liabilities embedded, for instance, in workers' pension plans, health care, private assistance and insurance, bonuses, ESOP incentives and so forth.

Over time, aspects like internal governance, environmental compliance and liquidity have become crucial. Despite the



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effort in creating an objective basis for rating assignment, the agency rating 'is, in the end, an opinion. The rating experience is as much an art as it is a science' (Standard & Poor's, 1998, Foreword).

Under these considerations, it is worth noting that the rating process is very complex and is typically structured as follows: preliminary analysis, meetings with the counterparty under scrutiny, preparation of a rating dossier submitted by the Analytical Team to the Rating Committee (usually composed of 5–7 voting members), new detailed analysis if needed, final approval by the Rating Committee, official communication to and subsequent meeting with the counterparty, and, if necessary, a new approval process and rating submission to the Rating Committee. Moreover, the rating is not directly determined by ratios; for instance, the more favorable the business risk, the higher the financial leverage compatible with a given rating class (Table 4-1).

Generally speaking, favorable positions in some areas could be counterbalanced by less favorable positions in others, with some transformation criteria: financial ratios are not intended to be hurdle rates or prerequisites that should be achieved to attain a specific debt rating. Average ratios per rating class are *ex post* observations and not *ex ante* guidelines for rating assignment.

The rating industry has changed over time because of consolidation processes that have left only three big international players. It is worth noting that three competitors have different rating definitions. Moody's releases mainly issues ratings and far less issuers' ratings. On the contrary, S&P concentrates on providing a credit quality valuation referred to the issuer, despite the fact that the counterparty could be selectively insolvent on public listed bonds or on private liabilities. The company FITCH adopts an intermediate solution, offering an issuer rating, limited to the potential insolvency on publicly listed bonds, without considering the counterparty's private and commercial bank borrowings. Therefore, ratings released by the three international rating agencies are not directly comparable. This was clearly seen when, in the United Kingdom, British Railways defaulted and was privatized, while the outstanding debt was immediately covered by state guarantee. British Railways issues were set in 'selective default' by S&P while (coherently) having remained 'investment grade' for Moody's and 'speculative grade' for FITCH. In recent years, nonetheless, market pressure urged agencies to produce more comparable ratings, increasingly built on quantitative analyses, beyond qualitative ones, adopting a wider range of criteria. In particular, after the 'Corporate America scandals' (ENRON is probably the most renowned), new criteria were introduced, such as the so called 'Core earnings methodology' on treatment of stock options, multi annual revenues, derivatives and off-balance sheet exposures and so on. Liquidity profiles were also adopted to assess the short term liquidity position of firms, as well as the possibility to dismantle some investments or activities in case of severe recession and so forth. New corporate governance rules were also established with reference to conflict of interests, transparency, the quality of board members, investors' relations, minorities' rights protections and so on. Monitoring was enhanced and market signals (such as market prices on listed bonds and stocks) were taken into further consideration.

**TABLE 4-1** Financial Leverage (Debt/Capital, in Percentage), Business Risk Levels and Ratings

| Company Business Risk Profile \ Rating Category | | AAA | AA | A | BBB | BB |
|---|---|---|---|---|---|---|
| Excellent | | 30 | 40 | 50 | 60 | 70 |
| Above average | | 20 | 25 | 40 | 50 | 60 |
| Average | | | 15 | 30 | 40 | 55 |
| Below average | | | | 25 | 35 | 45 |
| Vulnerable | | | | | 25 | 35 |

*Source:* Standard & Poor's (1998), page 19.



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## From Borrower Ratings to Probabilities of Default

The broad experience in rating assignment by agencies and the established methodology applied allow agencies to pile up a huge amount of empirical evidence about their judgments on predicted default rates. Until the 1990s, these data were only available for agencies' internal purposes; since then, these databases have also been sold to external researchers and became public throughout the credit analysts communities. Periodic publications followed, improving timeliness and specifications over time. Table 4-2 shows figures offered by Moody's rating agency on non-financial companies.

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**TABLE 4-2** Average Cumulated Annual Default Rates per Issues Cohorts, 1998/2007

| | Average Cumulated Annual Default Rates at the End of Each Year (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Initial Rating** | **Year 1** | **Year 2** | **Year 3** | **Year 4** | **Year 5** | **Year 6** | **Year 7** | **Year 8** | **Year 9** | **Year 10** |
| Aaa | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa2 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Aa3 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.06 | 0.17 | 0.17 | 0.17 | 0.17 |
| A1 | 0.00 | 0.00 | 0.00 | 0.00 | 0.04 | 0.06 | 0.06 | 0.06 | 0.06 | 0.06 |
| A2 | 0.05 | 0.11 | 0.25 | 0.35 | 0.46 | 0.52 | 0.52 | 0.52 | 0.52 | 0.52 |
| A3 | 0.05 | 0.19 | 0.33 | 0.43 | 0.52 | 0.54 | 0.54 | 0.54 | 0.54 | 0.54 |
| Baa1 | 0.21 | 0.49 | 0.76 | 0.90 | 0.95 | 1.04 | 1.26 | 1.58 | 1.66 | 1.66 |
| Baa2 | 0.19 | 0.46 | 0.82 | 1.31 | 1.66 | 1.98 | 2.21 | 2.35 | 2.58 | 2.58 |
| Baa3 | 0.39 | 0.93 | 1.54 | 2.21 | 3.00 | 3.42 | 3.85 | 4.33 | 4.49 | 4.49 |
| Ba1 | 0.43 | 1.26 | 2.11 | 2.49 | 3.16 | 3.65 | 3.68 | 3.68 | 3.68 | 3.68 |
| Ba2 | 0.77 | 1.71 | 2.81 | 4.03 | 4.78 | 5.06 | 5.45 | 6.48 | 7.53 | 10.16 |
| Ba3 | 1.06 | 3.01 | 5.79 | 8.52 | 10.24 | 11.76 | 13.25 | 14.67 | 16.12 | 17.79 |
| B1 | 1.71 | 5.76 | 10.21 | 14.07 | 17.14 | 19.59 | 21.21 | 23.75 | 26.61 | 28.37 |
| B2 | 3.89 | 8.85 | 13.69 | 18.07 | 20.57 | 23.06 | 26.47 | 28.52 | 30.51 | 32.42 |
| B3 | 6.18 | 13.24 | 21.02 | 27.63 | 33.35 | 39.09 | 42.57 | 45.19 | 48.76 | 51.11 |
| Caa1 | 10.54 | 20.90 | 30.39 | 38.06 | 44.46 | 48.73 | 50.51 | 50.51 | 50.51 | 50.51 |
| Caa2 | 18.98 | 29.51 | 37.24 | 42.71 | 44.99 | 46.83 | 46.83 | 46.83 | 46.83 | 46.83 |
| Caa3 | 25.54 | 36.94 | 44.01 | 48.83 | 54.04 | 54.38 | 54.38 | 54.38 | 54.38 | 54.38 |
| Ca-C | 38.28 | 50.33 | 59.55 | 62.49 | 65.64 | 66.26 | 66.26 | 66.26 | 66.26 | 100.00 |
| Investment Grade | 0.10 | 0.25 | 0.43 | 0.61 | 0.77 | 0.88 | 0.99 | 1.08 | 1.13 | 1.13 |
| Speculative Grade | 4.69 | 9.27 | 13.70 | 17.28 | 19.79 | 21.77 | 23.27 | 24.64 | 26.04 | 27.38 |
| All Rated | 1.78 | 3.48 | 5.07 | 6.31 | 7.15 | 7.76 | 8.22 | 8.62 | 8.99 | 9.28 |

*Source:* Moody's (2008).



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The basic principles at the foundation of these calculations are very straightforward:

- in the long run, given a homogenous population, actual frequencies converge to the central probability estimated, because of the law of large numbers (the average of the results obtained from a large number of trials should be close to the expected value, and will tend to become closer as more trials are performed);
- in the long run, if the population is homogeneous enough, actual frequencies are a good prediction of central probabilities.

In this perspective, when observations are averaged over time, probabilities could be inferred from the observation of average actual frequencies of default per rating class; these probabilities can be applied to infer the future of the population's behavior.

The availability of agencies' data also allows the calculation of the so-called migration frequencies, that is, the frequency of transition from one rating class to another; they offer an assessment of the 'migration risk', which has already been defined in the previous chapter. Tables 4-3 and 4-4 give examples of these migration matrices from Moody's publications: at the intersect of rows and columns there are relative frequencies of counterparties that have moved from the rating class indicated in each row to the rating class indicated in each column (as a percentage of the number of counterparties in the initial rating class).

The acronym WR denotes 'withdrawn ratings', which are the ratings that have been removed for various reasons, only excluding default (to investigate this aspect further, see Gupton, Finger, and Batia, 1997, or de Servigny and Renault, 2004).

The measures currently used by 'fixed income' market participants are based on:

- names: the number of issuers;
- Def: the number of names that have defaulted in the time horizon considered;
- PD: probability of default.

The default frequency in the horizon $k$, which is $[t, (t + k))$, is defined as:

$$PD_{\text{time horizon } k} = \frac{Def_t^{t+k}}{Names_t}$$

Given the sequence of default rates for a given issuers' class, the cumulated default frequency on horizon $k$ is defined as:

$$PD_{\text{time horizon } k}^{\text{cumulated}} = \frac{\sum_{i=t}^{i=t+k} DEF_i}{Names_t}$$

and the marginal default rate on the $[t, (t + k)]$ horizon is defined as:

$$PD_k^{\text{marg}} = PD_{t+k}^{\text{cumulated}} - PD_t^{\text{cumulated}}$$

**TABLE 4-3** One-Year Moody's Migration matrix (1970–2007 Average)

| | | Final Rating Class (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | **Aaa** | **Aa** | **A** | **Baa** | **Ba** | **B** | **Caa** | **Ca_C** | **Default** | **WR** |
| **Initial Rating Class** | Aaa | 89.1 | 7.1 | 0.6 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 3.2 |
| | Aa | 1.0 | 87.4 | 6.8 | 0.3 | 0.1 | 0.0 | 0.0 | 0.0 | 0.0 | 4.5 |
| | A | 0.1 | 2.7 | 87.5 | 4.9 | 0.5 | 0.1 | 0.0 | 0.0 | 0.0 | 4.1 |
| | Baa | 0.0 | 0.2 | 4.8 | 84.3 | 4.3 | 0.8 | 0.2 | 0.0 | 0.2 | 5.1 |
| | Ba | 0.0 | 0.1 | 0.4 | 5.7 | 75.7 | 7.7 | 0.5 | 0.0 | 1.1 | 8.8 |
| | B | 0.0 | 0.0 | 0.2 | 0.4 | 5.5 | 73.6 | 4.9 | 0.6 | 4.5 | 10.4 |
| | Caa | 0.0 | 0.0 | 0.0 | 0.2 | 0.7 | 9.9 | 58.1 | 3.6 | 14.7 | 12.8 |
| | Ca-C | 0.0 | 0.0 | 0.0 | 0.0 | 0.4 | 2.6 | 8.5 | 38.7 | 30.0 | 19.8 |

*Source:* Moody's (2008).

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**TABLE 4-4** Five-Year Moody's Migration Matrix (1970–2007 Average)

| Cohort Rating | | Final Rating Class (%) | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Aaa | Aa | A | Baa | Ba | B | Caa | Ca_C | Default | WR |
| Initial Rating Class | Aaa | 52.8 | 24.6 | 5.5 | 0.3 | 0.3 | 0.0 | 0.0 | 0.0 | 0.1 | 16.3 |
| | Aa | 3.3 | 50.4 | 21.7 | 3.3 | 0.6 | 0.2 | 0.0 | 0.0 | 0.2 | 20.3 |
| | A | 0.2 | 7.9 | 53.5 | 14.5 | 2.9 | 0.9 | 0.2 | 0.0 | 0.5 | 19.4 |
| | Baa | 0.2 | 1.3 | 13.7 | 46.9 | 9.4 | 3.0 | 0.5 | 0.1 | 1.8 | 23.2 |
| | Ba | 0.0 | 0.2 | 2.3 | 11.6 | 27.9 | 11.7 | 1.4 | 0.2 | 8.4 | 36.3 |
| | B | 0.0 | 0.1 | 0.3 | 1.5 | 7.2 | 21.8 | 4.5 | 0.7 | 22.4 | 41.5 |
| | Caa | 0.0 | 0.0 | 0.0 | 0.9 | 2.2 | 6.7 | 6.3 | 1.0 | 42.9 | 40.0 |
| | Ca-C | 0.0 | 0.0 | 0.0 | 0.0 | 0.3 | 2.3 | 1.5 | 2.5 | 47.1 | 46.3 |

*Source:* Moody's (2008).

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Finally, in regard to a future time horizon $k$, the 'forward probability' that is contingent to the survival rate at time $t$ is defined as:

$$PD_{t;t+k}^{Forw} = \frac{(Def_{t+k} - Def_t)}{Names\ survived_t} = \frac{PD_{t+k}^{cumulated} - PD_t^{cumulated}}{1 - PD_t^{cumulated}}$$

Some relationships among these definitions can be examined further. The cumulated default rate $PD^{cumulated}$ may be calculated using forward probabilities ($PD^{forw}$) through the calculation of the 'forward survival rates' ($SR^{forw}_{t;\,t+k}$). These are the opposite (i.e., the complement to 1) of the $PD^{forw}$, and are as follows:

$$PD_t^{cumulated} = 1 - [(1 - PD_1^{forw}) \times (1 - PD_2^{forw}) \times (1 - PD_3^{forw}) \times (1 - PD_4^{forw}) \times \ldots \times (1 - PD_n^{forw})]$$

If:

$$SR_{t;t+k}^{forw} = \left(1 - PD_{t;t+k}^{forw}\right)$$

then, the cumulated default rate can be expressed by the survival rates as:

$$PD_t^{cumulated} = 1 - \prod_{i=1}^{t} SR_i^{forw} \quad \text{and} \quad \left(1 - PD_t^{cumulated}\right) = \prod_{i=1}^{t} SR_i^{forw}$$

The 'annualized default rate' (ADR) can also be calculated. If it is necessary to price a credit risk exposed transaction on a five year time horizon, it is useful to reduce the five-year cumulated default rate to an annual basis for the purposes of calculation. The annualized default rate can be calculated by solving the following equation:

$$\left(1 - PD_t^{cumulated}\right) = \prod_{i=1}^{t} SR_i^{forw} = (1 - ADR_t)^t$$

Hence, the discrete time annualized default rate is:

$$ADR_t = 1 - \sqrt[t]{\prod_{i=1}^{t} SR_i^{forw}} = 1 - \sqrt[t]{(1 - PD_t^{cumulated})}$$

Whereas, the continuous annual default rate is:

$$1 - PD_t^{cumulated} = e^{-ADR_{t \times t}}$$

and consequently:

$$ADR_t = -\frac{\ln(1 - PD_t^{cumulated})}{t}$$

This formula gives the measure of a default rate, which is constant over time and generates the same cumulated default rate observed at the same maturity that was extracted from the empirical data.

Table 4-5 gives an example of the relationships between different measures that have been outlined above.



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**TABLE 4-5** Example of Default Frequencies for a Given Rating Class

| | Years | | | | | |
|---|---|---|---|---|---|---|
| | 1 | 2 | 3 | 4 | 5 | |
| **names$_{t=0}$** | **1000** | | | | | |
| **names$_t$** | **990** | **978** | **965** | **950** | **930** | |
| **default$_{cumulated;\,t}$** | **10** | **22** | **35** | **50** | **70** | **Formulas** |
| $PD^{cumulated}$, % | 1.00 | 2.20 | 3.50 | 5.00 | 7.00 | $PD_k^{cumulated} = \frac{\sum_t^{t+k} DEF_i}{Names_{t=0}}$ |
| $PD_k^{marg}$, % | 1.00 | 1.20 | 1.30 | 1.50 | 2.00 | $PD_K^{marg} = PD_{t+k}^{cumulated} - PD_t^{cumulated}$ |
| $PD_k^{forw}$, % | 1.00 | 1.21 | 1.33 | 1.55 | 2.11 | $PD_k^{Forward} = \frac{(Def_{t+k} - Def_t)}{Names\ survived_t}$ |
| $SR_t^{cumul}$, % | 99.00 | 97.80 | 96.50 | 95.00 | 93.00 | $SR_t^{cumul} = \left(1 - PD_t^{cumulated}\right)$ |
| $SR_k^{forw}$, % | 99.00 | 98.80 | 98.70 | 98.50 | 98.00 | $SR_k^{forw} = \left(1 - PD_k^{forw}\right)$ |
| $ADR_{t\ discrete\ time}$, % | 1.00 | 1.11 | 1.18 | 1.27 | 1.44 | $ADR_t = 1 - \sqrt[t]{(1 - PD_t^{cumulated})}$ |
| $ADR_{t\ continuous\ time}$, % | 1.01 | 1.11 | 1.19 | 1.28 | 1.45 | $ADR_t = -\frac{\ln(1 - PD_t^{cumulated})}{t}$ |

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With regard to the two final formulas, it must be borne in mind that they are shortcuts to solve pricing (and credit risk valuation) problems. In reality, it must be remembered that paths to default are not a steady and continuous process, but instead the paths to default present discontinuities and co-dependent events. Migrations are not ‘Brownian random walks’, but rather dependent and correlated transitions from one class to another over time. Moreover, credit quality and paths to default are managed both by counterparties and lenders. Actual observations prove that ratings become better than expected if the initial classes are low (bad) and, conversely, they become worse than expected if the initial classes are very high (good). These considerations have to be clearly taken into account when analyzing counterparties and markets, or when tackling matters such as defining the optimal corporate financial structure, performing a credit risk valuation or even measuring the risk of a credit portfolio.

Despite the fact that these methodologies are occasionally very complex and advanced, it is worth noting that default frequencies obviously have their limitations. They are influenced by the methodological choices of different rating agencies because:

- definitions are different through various rating agencies, so frequencies express dissimilar events;
- populations that generate observed frequencies are also different. As a matter of fact, many counterparts have only one or two official ratings, neglecting one or two of the other rating agencies;
- amounts rated are different, so when aggregated using weighted averages, the weights applied are dissimilar;
- initial rating for the same counterparts released by different rating agencies are not always similar.



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Furthermore, official rating classes are an ordinal ranking, not a cardinal one: 'triple B' counterparty has a default propensity higher than a 'single A' and lower than a 'double B'. Actual default frequencies are only a proxy of this difference, not a rigorous statistical measure. Actual frequencies are only a surrogate of default probability. Over time, rating agencies have added more details to their publications and nowadays they also provide standard deviations of default rates observed over a long period. The variation coefficient, calculated using this data (standard deviation divided by mean), is really high through all the classes, mostly in the worst ones, which are highly influenced by the economic cycle. The distribution's fourth moment is high, showing a very large dispersion with fat tails and large probability of overlapping contiguous classes. Nevertheless, agencies' ratings are, *ex post,* the most performing measures among the available classifications for credit quality purposes.

## Experts-Based Internal Ratings Used by Banks

As previously mentioned, banks' internal classification methods have different backgrounds from agencies' ratings assignment processes. Nevertheless, sometimes their underlying processes are analogous; when banks adopt judgmental approaches to credit quality assessment, the data considered and the analytical processes are similar. Beyond any opinion on models' validity, rating agencies put forward a sound reference point to develop various internal analytical patterns. For many borrower segments, banks adopt more formalized (that is to say model based) approaches. Obviously, analytical solutions, weights, variables, components, and class granularities are different from one bank to another. But market competition and syndicated loans are strong forces leading to a higher convergence. In particular, where credit risk market prices are observable, banks tend to harmonize their valuation tools, favoring a substantial convergence of methods and results.

In principle, there is no proven inferiority or superiority of expert-based approaches versus formal ones, based on quantitative analysis such as statistical models. Certainly, judgment-based schemes need long lasting experience and repetitions, under a constant and consolidated method, to assure the convergence of judgments. It is very difficult to reach a consistency in this methodology and in its results because:

- organizational patterns are intrinsically dynamic, to adapt to changing market conditions and bank's growth, conditions that alter processes, procedures, customers' segments, organization appetite for risk and so forth;
- mergers and acquisitions that blend different credit portfolios, credit approval procedures, internal credit underwriting powers and so forth;
- over time, company culture will change, as well as experts' skills and analytical frameworks, in particular with reference to qualitative information.

Even if the predictive performances of these methods (read by appropriate accuracy measures) are good enough in a given period, it is not certain that the same performance will be reached in the future. This uncertainty could undermine the delicate and complex management systems that are based on internal rating systems in modern banking and financial organizations.

An assessment of the main features of expert-based rating systems along the three principles that have been previously introduced is proposed in Table 4-6.

**TABLE 4-6** Summary of the Main Features of Expert-Based Rating Systems

| Criteria | Agencies' Ratings | Internal Experts-Based Rating Systems |
|---|---|---|
| Measurability and verifiability | ◕ | ◔ |
| Objectivity and homogeneity | ◕ | ◑ |
| Specificity | ● | ◕ |

The circle is a measure of adequacy: full when completely compliant, empty if not compliant at all. Intermediate situations show different degrees of compliance.

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## STATISTICAL-BASED MODELS

### Statistical-Based Classification

A quantitative model is a controlled description of certain real world mechanics. Models are used to explore the likely consequences of some assumptions under various circumstances. Models do not reveal the truth but are merely expressing points of view on how the world will probably behave. The distinctive features of a quantitative financial model are:

- the formal (quantitative) formulation, that explains the simplified view of the world we are trying to catch;
- the assumptions made to build the model, that set the foundation of relations among variables and the boundaries of the validity and scope of application of the model.

Generally speaking, the models which are employed in finance are based on simplifying assumptions about the phenomena that it is wished to predict; they should incorporate the vision of organizations' behavior, the possible economic events, and the reactions of market participants (that are probably using other models). Quantitative financial models therefore embody a mixture of statistics, behavioral psychology, and numerical methods.

Different assumptions and varying intended uses will, in general, lead to different models, and in finance, as in other domains, those intended for one use may not be suitable for other uses. Poor performance does not necessarily indicate defects in a model but rather that the model is used outside its specific realm. Consequently, it is necessary to define the type of models that are examined in the following pages very clearly. The models described in this book are mainly related to the assessment of default risk of unlisted firms, in effect, the risk that a counterparty may become insolvent in its obligations within a pre-defined time horizon. Generally speaking, this type of model is based on low frequency and non-publicly available data as well as mixed quantitative and qualitative variables. However, the methods proposed may also be useful in tackling the default risk assessment for large corporations, financial institutions, special purpose vehicles, government agencies, non-profit organizations, small businesses, and consumers. Also briefly touched upon are the credit risk valuation methods for listed financial and non-financial companies, briefly outlining the Merton approach.

The access to a wider range of quantitative information (mainly, but not only, from accounting and financial reports) pressured many researchers since the 1930s to try to generate classifications using statistical or numerical methodologies. In the mid 1930s, Fisher (1936) developed some preliminary applications. At the end of the 1960s, Altman (1968) developed the first scoring methodology to classify corporate borrowers using discriminant analysis; this was a turning point for credit risk models.

In the following decades, corporate scoring systems were developed in more than 25 industrial and emerging countries. Scoring systems are part of credit risk management systems of many banks from western countries, as stated in a survey by the Basel Committee (2000b). To give an example of a non-Anglo-Saxon country, groundwork in this field was carried out in Italy during the late 1970s and early 1980s. In the early 1980s, the Financial Report Bureau was founded in Italy by more than 40 Italian banks; its objective was to collect and mutually distribute financial information about industrial Italian private and public limited companies. The availability of this database allowed the Bureau to develop a credit scoring model used by these banks during the 1980s and the 1990s. Nowadays, the use of quantitative methodologies is applied to the vast majority of borrowers and to ordinary lending decisions (De Laurentis, Saita and Sironi, 2004; Albareto et al., *2008).*

The first step in describing alternative models is to distinguish between structural approaches and reduced form approaches.

### Structural Approaches

Structural approaches are based on economic and financial theoretical assumptions describing the path to default. Model building is an estimate (similar to that of econometric models) of the formal relationships that associate the relevant variables of the theoretical model. This is opposite to the reduced form models, in which the final solution is reached using the most statistically suitable set of variables and disregarding the theoretical and conceptual causal relations among them.

This distinction became very apparent after the Merton (1974) proposal: default is seen as a technical event that occurs when the company's proprietary structure is no longer worthwhile. From the early 1980s, Merton's suggestion became widely used, creating a new foundation for credit risk measurements and analysis. According to this



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vision, cash flows out of a credit contract have the same structure as a European call option. In particular, the analogy implies the following:

- when the lender underwrites the contract, he is given the right to take possession of the borrower's assets if the borrower becomes insolvent;
- the lender sells a call option on the borrower's assets to the borrower, having the same maturity as debt, at the strike price equal to debt face value;
- at debt maturity, if the value of borrower's assets exceeds the debt face value, the borrower will pay the debt and shall retain full possession of his assets; otherwise, where the assets value is lower than the debt face value, the borrower has the convenience of missing debt payment and will resultantly lose possession of his assets.

This vision is very suggestive and offers workable solutions to overcome many analytical credit risk problems:

- By using a definition of default that is dependent on financial variables (market value of assets, debt amount, volatility of asset values) the Black Scholes Merton formula can be used to calculate default probability. There are five relevant variables: the debt face value (option strike), assets value (underlying option), maturity (option expiration date), assets value volatility (sigma), and market risk interest rate (for alternatives see Vasicek, 1984). This solution provides the probability that the option will be exercised, that is, the borrower will be insolvent.
- This result is intrinsically probabilistic. The option exercise depends on price movements and utility functions of the contract underwriters, hence from the simultaneous dynamics of the variables mentioned above. No other variables (such as macroeconomic conditions, legal constraints, jurisdictions, and default legal definitions) are implied in the default process.
- The default event is embedded in the model and is implicit in economic conditions at debt maturity.
- The default probability is not determined in a discrete space (as for agencies' ratings) but rather in a continuous space based on the stochastic dispersion of asset values against the default barrier, that is, the debt face value.

Merton's model is therefore a cause-and-effect approach: default prediction follows from input values. In this sense, Merton's model is a 'structural approach', because it provides analytical insight into the default process. Merton's insight offers many implications. The corporate equity is seen as a derivative contract, that is to say, the approach also offers a valuable methodology to the firm and its other liabilities. Moreover, as already stated, the option values for debt and equity implicitly include default probabilities to all horizons. This is a remarkable innovation in respect to the deductions of Modigliani and Miller. According to these two authors, the market value of the business ('assets') is equal to the market value of the fixed liabilities plus the market value of the equity; the firm financial structure is not related to the firm's value if default costs are negligible. The process of business management is devoted to maximizing the firm's value; the management of the financial structure is devoted to maximizing shareholders' value. No conflict ought to exist between these two objectives. In the Merton approach to the firm's financial structure, the equity is a call option on the market value of the assets. Thus, the value of the equity can be determined from the market value of the assets, the volatility of the assets, and the book value of the liabilities. That is to say, the business risk and the financial risk (assumed as independent risk by Modigliani and Miller) are simultaneously linked to one another by the firm's asset volatility. The firm's risk structure determines the optimal financial structure solution, which is based on the business risk profile and the state of the financial environment (interest rates, risk premium, equity and credit markets, investors' risk appetite).

More volatile businesses imply less debt/equity ratios and vice versa. The choice of the financial structure has an impact on the equity value because of the default probability (that is the probability that shareholders will lose their investments).

Following the Merton approach and applying Black Scholes Merton formula, the default probability is consequently given by:

$$PD = N\left(\frac{\ln(F) - \ln(V_A) - \mu T + \frac{1}{2}\sigma_A^2}{\sigma_A\sqrt{T}}\right)$$

where ln is the natural logarithm, $F$ is the debt face value, $V_a$ is the firm's asset value (equal to the market value of equity and net debt), $\mu$ is the 'risky world' expected

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return,[1] $T$ is the remaining time to maturity, $\sigma_a$ is the instantaneous assets value volatility (standard deviation), $N$ is the cumulated normal distribution operator.

[1] It is worth noting that the Black Scholes formula is valid in a risk neutral world. Hence the solution offers risk neutral probabilities. Here we are interested in real world (or so called 'physical') default probability because we are not interested in pricing debt but in describing actual defaults. To pass from actual to risk neutral default probabilities, a calculation is needed. The value of a credit contract can be defined as:

$$V_F = C_o e^{-rt}(1 - q_t \omega)$$

in which $V$ = credit market value of contract, $C_t$ = initial credit face value, $\alpha\upsilon\delta\omega$ = loss given default. Using Black Scholes formula, it is possible to define:

$$q_{\text{risk neutral world}} = N(-Z)$$
$$P_{\text{real world}} = N(-Z')$$

in which

$$Z = \frac{\left[\ln\left(\frac{V}{D}\right) + r_{\text{risk free}} - \frac{\sigma^2}{2}\right]}{\sigma_v}; \quad Z' = \frac{\left[\ln\left(\frac{V}{D}\right) + \textit{risky world}\right] - \frac{\sigma^2}{2}}{\sigma_v}$$

so:

$$q = N\left\{N^{-1}(p) + \frac{r_{\text{risky world}} - r_{\text{risk free}}}{\sigma_v}\right\}$$

But, from the Capital Asset Pricing Model theory, denoting the market risk premium as *mrp:*

$$r_{\text{risky world}} = r_{\text{risk free}} + \beta(mrp)$$
$$\beta = \frac{\text{cov}}{\text{var}_{mrp}}$$

then:

$$\frac{r_{\text{risky world}} - r_{\text{risk free}}}{\sigma_v} = \beta\frac{(mrp)}{\sigma_v} = \frac{\text{cov}}{\sigma^2_{mrp}} \times \frac{(mrp)}{\sigma_v}$$
$$= \frac{\text{cov}}{\sigma_v \times \sigma_{mrp}} \times \frac{(mrp)}{\sigma_{mrp}} \rho_{\text{firm values; mrp}} \lambda$$

in which $\lambda$ is the Market Sharpe ratio. Subsequently, $q = N\{N^{-1}(p) - \rho\lambda\}$.

Upon deriving from market data *C, r, t, LGD*, $p_t$ and $\rho$, it is possible to estimate $\lambda$ on high frequency basis. The estimate of $\lambda$ is quite stable over time (it suggests that spread variation is driven by *PD* variation, not risk premium). On the contrary, knowing $\lambda$, 'real world' default probability could be calculated starting from bond or CDS market prices.

The real world application of Merton's approach was neither easy nor direct. A firm's asset value and asset value volatility are both unobservable; the debt structure is usually complex, piling up many contracts, maturities, underlying guarantees, clauses and covenants. Black Scholes formula is highly simplified in many respects: interest rates, volatilities, and probability density functions of future events.

A practical solution was found in the early 1980s observing that the part in brackets of the mathematical expression described above is a standardized measure of the distance to the debt barrier, that is, the threshold beyond which the firm goes into financial distress and default. This expression is then transformed into a probability by using the cumulated normal distribution function.

In addition, there is a relation (Itô, 1951) linking equity and asset value, based on their volatilities and the 'hedge ratio' of the Black Scholes formula. It has the form:

$$\sigma_{\text{equity}} E_0 = N(d_1)\sigma_{\text{asset value}} V_0$$

For listed companies on the stock market, equity values and equity volatilities are observable from market prices. Thus, this expression is absolutely relevant, as it allows calculation of asset values and asset values' volatility when equity market prices are known. A system of two unknown variables ($V_a$ and $\sigma_a$) and two independent equations (the Black Scholes formula and Itô's lemma) has a simultaneous mathematical solution in the real numerical domain.

Therefore, the distance to default (*DtD*) can be calculated (assuming $T = 1$) as follows (Bohn, 2006):

$$DtD = \frac{\ln V_a - \ln F + \left(\mu_{\text{risky}} - \frac{\sigma_a^2}{2}\right) - \text{'other payouts'}}{\sigma_a} \cong \frac{\ln V - \ln F}{\sigma_a}$$

The default probability can be determined starting from this solution and using econometric calibration, even in continuous time, following the movements of equity prices and interest rates on the capital market. Despite the elegant solution offered by Merton's approach, in real world applications the solution is often reached by calibrating *DtD* on historical series of actual defaults. The KMV Company, established by McQuown, Vasicek and Kealhofer, uses a statistical solution utilizing *DtD* as an explanatory variable to actual defaults. Solutions using



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statistical probability density functions (normal, lognormal or binomial) were found to be unreliable in real applications. These observations led Perraudin and Jackson (1999) to classify, also for regulatory purposes, Merton-based models as a scoring models.

*DtD* is a very powerful indicator that could also be used as an explicative variable in econometric or statistical models (mainly based on linear regression) to predict default probabilities.

These applications gained a huge success in the credit risk management world in order to rate publicly listed companies. Merton's approach is at the foundation of many credit trading platforms (supporting negotiations, arbitrage activities, and valuations) and tools for credit pricing, portfolio management, credit risk capital assessment, risk adjusted performance analysis, limit setting, and allocation strategies. Its main limit is that it is applicable only to liquid, publicly traded names. Also, in these cases, there is a continuous need for calibration; therefore, a specific maintenance is required. Small organizations cannot afford these analytical requirements, while nave approaches are highly unadvisable because of the great sensitivity of results to parameters and input measures.

Attempts were made to extend this approach to unlisted companies. Starting from the early 2000s, after some euphoria, these attempts were abandoned because of unavoidable obstacles. The main obstacles are:

- Prices are unobservable for unlisted companies. Using proxies or comparables, the methodology is very sensitive to some key parameters which causes results to become very unreliable.
- The use of comparables prices is not feasible when companies under analysis are medium sized enterprises. Comparables market prices become very scarce, smaller companies have very high specificity (their business is related to market niches or single production segments, largely idiosyncratic). In these circumstances, values and volatilities are very difficult to come across in a reliable way.

In comparison to agencies' ratings, Merton's approaches are:

- more sensitive to market movements and quicker and more accurate in describing the path to default;
- far more unstable (because of continuative movements in market prices, volatility, and interest rates). This aspect is not preferred by long term institutional investors that like to select investments based on counterparties' fundamentals, and dislike changing asset allocation too frequently.

Tarashev (2005) compared six different Merton-based structural credit risk models in order to evaluate the performance empirically, confronting the probabilities of default they deliver to *ex post* default rates. This paper found that theory-based default probabilities tend to closely match the actual level of credit risk and to account for its time path. At the same time, because of their high sensitivity, these models fail to fully reflect the dependence of credit risk on the business and credit cycles. Adding macro variables from the financial and real sides of the economy helps to substantially improve the forecasts of default rates.

## Reduced Form Approaches

Reduced form models as opposed to structural models make no *ex ante* assumptions about the default causal drivers. The model's relationships are estimated in order to maximize the model's prediction power: firm characteristics are associated with default, using statistical methodologies to associate them to default data.

The default event is, therefore, exogenously given; it is a real life occurrence, a file in some bureau, a consequence of civil law, an official declaration of some lender, and/or a classification of some banks.

Independent variables are combined in models based on their contribution to the final result, that is, the default prediction on a pre-defined time horizon. The set of variables in the model can change their relevance in different stages of the economic cycle, in different sectors or for firms of different sizes. These are models without (or with a limited) economic theory, they are a sort of 'fishing expedition' in search of workable solutions.

The following is a practical example.

Suppose that the causal path to default is as follows: competitive gap → reduction in profitability margins → increase in working capital requirements (because of a higher increase in inventories and receivables than in payables) → banks' reluctance to lend more → liquidity shortage → insolvency and formal default.

A structural approach applied to listed companies could perceive this path as follows: reduction in profitability →



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reduction in equity price → more uncertainty in future profitability expectations → more volatility in equity prices → reduction in enterprise value and an increase in asset value volatility → banks' reluctance in granting new credit → stable debt barrier → sharp and progressive DtD reduction → gradual increase in default probability → early warning signals of credit quality deterioration and diffusion to credit prices → credit spread amplification → market perception of technical default situation.

As can be seen, a specific cause–effect process is clearly depicted.

What about a reduced form model? Assume that the default model is based on a function of four variables: return on sales, net working capital on sales, net financial leverage, and banks' short term debt divided by total debt. These variables are simultaneously observed (for instance, at year-end). No causal effect could therefore be perceived, because causes (competitive gap and return on sales erosion) are mixed with effects (net working capital and financial leverage increases). However, the model suggests that when such situations simultaneously occur, a default may occur soon after. If a company is able to manage these new working capital requirements by longstanding relationships with banks and new financial borrowings, it could overcome the potential crisis. However, it would be more difficult in a credit crunch period than in normal times.

In reduced form approaches there is a clear model risk: models intrinsically depend on the sample used to estimate them. Therefore, the possibility to generalize results requires a good degree of homogeneity between the development sample and the population to which the model will be applied. It should be clear at this point that different operational, business and organizational conditions, local market structures, fiscal and accounting regimes, contracts and applicable civil laws, may produce very different paths to default. As a consequence, this makes it clear that a model estimated in a given environment may be completely ineffective in another environment.

To give an idea of the relevance of this observation, consider a survey carried out at SanpaoloIMI Bank (Masera, 2001). A random sample of 1000 customers was extracted from the commercial lending portfolio. These companies were rated using the internal rating model and, at the same time, applying the last release of Altman's scoring formula (based on discriminant analysis, which will be extensively examined in the following paragraph). The purpose was to assess if:

- external models could be introduced in the banking organization without adaptation;
- variables proven to be relevant in external applications could also be useful to develop internal models, only making up coefficients and parameters.

The outcomes were very suggestive. When the classifications were compared, only 60% of good ratings were confirmed as good ratings by Altman's model, while 4% of these ratings were classified as being very close to defaulting by Altman's model. For bad rating classes, convergence was even lower or null. It could be considered that the problem was in model calibration and not in model structure: to overcome this objection, a new Altman-like model was developed, using the same variables but re-estimating parameters on the basis of the bank's internal sample. In this case, even if convergence was higher, results indicated that there was no chance to use the Altman-like model instead of the internal model. The main source of divergence was due to the role of variables that were highly country specific, such as working capital and liquidity ratios.

Therefore, these comparisons discourage the internal use of externally developed models: different market contexts require different analyses and models. This is not a trivial observation and there is, at the same time, a limitation and an opportunity in it:

- to develop an internal credit rating system is very demanding and requires much effort at both methodological and operational levels;
- to account on a reliable internal credit rating system is a value for the organization, a quality leap in valuation and analytical competence, a distinctive feature in competition.

When starting with a model building project, a strategic vision and a clear structural design at organizational level is required to adequately exploit benefits and advantages. The nature of the reduced form approaches impose the integration of statistics and quantitative methods with professional experience and qualitative information extracted from credit analysts from the initial stages of project development. In fact, even if these models are not



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based on relations expressing a causal theory of default, they have to be consistent with some theoretical economic expectation. For instance, if a profitability ratio is include in the model with a coefficient sign that indicates that the higher the ratio the higher default risk, we shall conclude that the model is not consistent with economic expectations.

Reduced form credit risk models could be classified into two main categories, statistical and numerical based. The latter comprises iterative algorithms that converge on a calibration useful to connect observed variables and actual defaults at some pre-defined minimum level of accuracy given the utility functions and performance measures. The former comprises models whose variables and relations are selected and calibrated by using statistical procedures.

These two approaches are the most modern and advanced. They are different from classifications based on the aggregation of various counterparts in homogeneous segments, defined by few counterparts' profiles (such as location, industry, sector, size, form of business incorporation, capitalization and so forth). These are referred to as 'top down' classifications because they segment counterparts based on their dominant profiles, without weighing variables and without combining them by specific algorithms; counterparts' profiles are typically categorical variables and they are used as a knife to split the portfolio into segments. Then, for each segment, the sample-based default rate will be used as an indicator of the probability of default for that segment of borrowers. Inversely, classification based on many variables whose values impact on results case by case are called 'bottom up.' Of course, there is a continuum between bottom up and top down approaches. Experts-based approaches are the most bottom up, but as they become more structured they reduce their capability of being case-specific. Numerical methods and statistical methods, even if highly mechanical, are considered as being 'quite' bottom up approaches because they take into account many variables characterizing the borrower (many of which are scale variables) and combine them by using specific algorithms.

An important family of statistical tools is usually referred to as scoring models; they are developed from quantitative and qualitative empirical data, determining appropriate variables and parameters to predict defaults. Today, linear discriminant analysis is still one of the most widely used statistical methods to estimate a scoring function.

## Statistical Methods: Linear Discriminant Analysis

Models based on linear discriminant analysis (LDA) are reduced form models because the solution depends on the exogenous selection of variables, group composition, and the default definition (the event that divides the two groups of borrowers in the development sample). The performance of the model is determined by the ability of variables to give enough information to carry out the correct assignment of borrowers to the two groups of performing or defaulting cases.

The analysis produces a linear function of variables (known as 'scoring function'); variables are generally selected among a large set of accounting ratios, qualitative features, and judgments on the basis of their statistical significance (i.e., their contribution to the likelihood of default). Broadly speaking, the coefficients of the scoring functions represent the contributions (weights) of each ratio to the overall score. Scores are often referred to as Z-score or simply Z.

Once a good discriminant function has been estimated using historical data concerning performing and defaulted borrowers, it is possible to assign a new borrower to groups that were preliminarily defined (performing, defaulting) based on the score produced by the function. The number of discriminant functions generated by the solution of a LDA application is $(k - 1)$, where $k$ is the groups' number (in our case there are two, so there is one discriminant function).

Over time, the method has become more and more composite because of variegated developments; today there is a multitude of discriminant analysis methods. From here onwards, reference is mainly to the Ordinary Least Square method, which is the classic Fisher's linear discriminant analysis, analogous with the usual linear regression analysis. The method is based on a min–max optimization: to minimize variance inside the groups and maximize variance among groups.

Primarily, LDA has taxonomical purposes because it allows the initial population to be split into two groups which are more homogenous in terms of default probability, specifying an optimal discriminant Z-score threshold to distinguish between the two groups. Nevertheless, the scoring function can also be converted into a probabilistic measure, offering the distance from the average features



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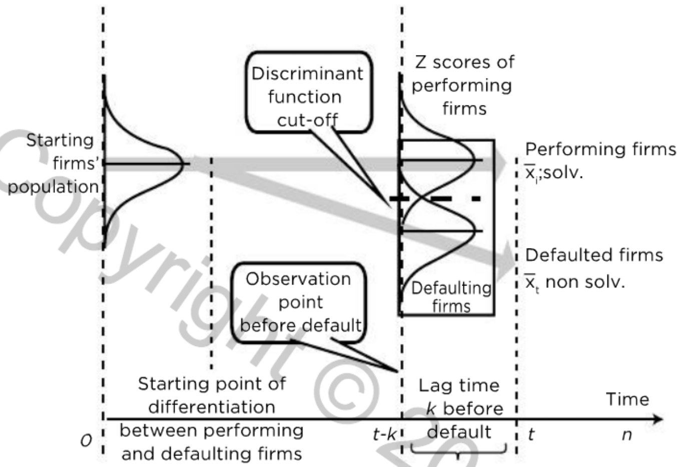


**FIGURE 4-4** A simplified illustration of a LDA model framework applied to default prediction.

of the two pre-defined groups, based on meaningful variables and proven to be relevant for discrimination.

The conceptual framework of reduced form models such as models based on LDA is summarized graphically in Figure 4-4. Let's assume that we are observing a population of firms during a given period. As time goes by, two groups emerge, one of insolvent (firms that fall into default) and the other of performing firms (no default has been filed in the considered time horizon: these are solvent firms). At the end of the period, there are two groups of well distinct firms: defaulted and performing firms. The problem is: given the firms' profile some time before the default (say *t-k*), is it possible to predict which firms will actually fall into default and which will not fall into default in the period between *t-k* and *t*?

LDA assigns a Z-score to each firm at time *t-k*, on the basis of available (financial and non-financial) information concerning firms. In doing so, the groups of firms that at time *t* will be solvent or insolvent are indicated at time *t-k* by their Z-scores distributions. The differentiation between the two distributions is not perfect; in fact, given a Z cut-off, some firms that will become insolvent have a score similar to solvent firms, and vice versa. In other words, there is an overlapping between Z scores of performing and defaulting firms and, for a given cut-off, some firms are classified in the wrong area. These are the model's errors that are minimized by the statistical procedure used to estimate the scoring function.

LDA was one of the first statistical approaches used to solve the problem of attributing a counterpart to a credit quality class, starting from a set of quantitative attributes. Altman (1968) proposed a first model, which was based on a sample of 33 defaulted manufacturing firms and the same number of non-defaulted firms. For each firm, 22 financial ratios were available in the dataset. The estimated model included five discriminant variables and their optimal discriminant coefficients:

$$Z = 1.21x_1 + 1.40x_2 + 3.30x_3 + 0.6x_4 + 0.999x_5$$

where $x_1$ is working capital/total assets, $x_2$ is accrued capital reserves/total assets, $x_3$ is EBIT/total assets, $x_4$ is equity market value/face value of term debt, $x_5$ is sales/total assets, and $Z$ is a number.

To understand the results, it is necessary to consider the fact that increasing Z implicates a more likely classification in the group of non-defaulted companies; therefore, all variables have coefficient signs aligned with financial theory. The discriminant threshold used to distinguish predicted defaulting from predicted performing companies is fixed at Z = 2.675 (also known as *cut-off value).*

A numerical example is shown in Table 4-7. Company ABC has a score of 3.19 and ought to be considered in a safety area. Leaving aside the independent variables' correlation (which is normally low) for the sake of simplicity, we can calculate the variables' contribution to the final result, as shown in Table 4-7.

We could also perform stress tests. For instance, if sales decrease by 10% and working capital requirements increase by 20% (typical consequence of a recession), the Z-score decreases to 2.77, which is closer to the cut-off point (meaning a higher probability of belonging to the default group). In these circumstances, the variables contribution for Company ABC will also change. For instance, the weight of working capital increases in the final result, changing from one-quarter to more than one-third; it gives, broadly speaking, a perception of elasticity to this crucial factor of credit quality. In particular, the new variables contribution to the rating of Company ABC will change as depicted in Table 4-8.

A recent application of LDA in the real world is the RiskCalc© model, developed by Moody's rating agency. It was specifically devoted to credit quality assessment of unlisted SMEs in different countries (Dwyer, Kocagil, and Stein, 2004). The model uses the usual financial



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**TABLE 4-7** Altman's Z-Score Calculation for Company ABC

| Asset & Liabilities/Equities | | | Profit & Loss Statement | | |
|---|---|---|---|---|---|
| Fixed Assets<br>Inventories<br>Receivables<br>Cash | 100<br>90<br>120<br>4 | *31.8%*<br>*28.7%*<br>*38.2%*<br>*1.3%* | Sales<br>EBITDA<br>Net Financial Expenses<br>Taxes | 500000<br>35000<br>9750<br>8333 | 100.0%<br>7.0%<br>2.0%<br>1.7% |
| | 314 | **100%** | Profit | 16918 | 3.4% |
| Capital<br>Accrued Capital Reserves<br>Financial Debts<br>Payables<br>Other Net Liabilities | 80<br>40<br>130<br>54<br>10 | *25.5%*<br>*12.7%*<br>*41.4%*<br>*17.2%*<br>*3.2%* | Dividends<br>Accrued Profits | 11335<br>5583 | 2.3%<br>1.1% |
| | 314 | **100%** | | | |
| Ratios for company ABC | (%) | Model coefficients | Ratio contributions for company ABC (%) | | |
| working capital/total assets | 68 | 1.210 | 25.8 | | |
| accrued capital reserves/ total assets | 13 | 1.400 | 5.6 | | |
| EBIT/total assets | 11 | 3.300 | 11.5 | | |
| equity market value/face value of term debt | 38 | 0.600 | 7.2 | | |
| sales/total assets | 159 | 0.999 | 49.9 | | |
| **Altman's Z-score** | | **3.191** | 100 | | |

**TABLE 4-8** New Variables Profile in a Hypothetical Recession for Company ABC

| **Ratios for Company ABC (%)** | | **Model Coefficients** | **Ratio Contributions for Company ABC (%)** |
|---|---|---|---|
| working capital/total assets | 72 | 1.210 | 31.4 |
| accrued capital reserves/total assets | 11 | 1.400 | 5.7 |
| EBIT/total assets | 8 | 3.300 | 10.0 |
| equity market value/face value of term debt | 34 | 0.600 | 7.3 |
| sales/total assets | 126 | 0.999 | 45.6 |
| **Altman's Z-score** | | **2.768** | 100.0 |



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information integrated by capital markets data, adopting a Merton approach as well. In this model (which is separately developed for many industrialized and emerging countries), the considered variables belong to different analytical areas, like profitability, financial leverage, debt coverage, growth, liquidity, assets, and size. To avoid overfitting effects and in an attempt to have a complete view of the potential default determinants, the model is forced to use at least one variable per analytical area.

The model is estimated on a country-by-country basis. In the case of Italy, we have realized that the model takes evidence from the usual drivers of judgmental approaches:

- higher profitability and liquidity ratios have a substantially positive impact on credit quality, while higher financial leverage weakens financial robustness;
- growth has a double faceted role: when it is both very high and negative, the probability of default increases;
- activity ratios are equally multifaceted in their effects: huge inventories and high receivables lead to default, while investments (both tangible and intangible) either reduce the default probability or are not influential;
- company size is relevant because the larger ones are less prone to default.

LDA therefore optimizes variables coefficients to generate *Z*-scores that are able to minimize the 'overlapping zone' between performing and defaulting firms. The different variables help one another to determine a simultaneous solution of the variables weights. This approach allows the use of these models for a large variety of borrowers, in order to avoid developing different models for different businesses, as it happens when structuring expert based approaches.

### Coefficient Estimation in LDA

Assume that we have a dataset containing $n$ observations (borrowers) described by $q$ variables (each variable called $x$), split in two groups, respectively of performing and defaulted borrowers. The task is to find a discriminant function that enables us to assign a new borrower $k$, described in its $x_k$ profile of $q$ variables, to the performing (solvent) or defaulting (insolvent) groups, by maximizing a predefined measure of homogeneity (statistical proximity).

We can calculate variables means in each group, respectively defined in the two vectors $\overline{x_{solvent}}$ and $\overline{x_{insolvent}}$, known as groups' 'centroids'. The new observation $k$ will then be assigned to either one or the other group on the basis of a minimization criterion, which is the following:

$$\min\left\{\sum_{i=1}^{q}\left(x_{i;k}-\overline{x_{i;solv/insolv}}\right)^2\right\}$$

or, in matrix algebra notation:

$$\min\left\{\left(x_k-\overline{x_{solv/insolv}}\right)'\left(x_k-\overline{x_{solv/insolv}}\right)\right\}$$

This expression could be geometrically interpreted as the Euclidean distance of the new observation $k$ to the two centroids (average profile of solvent and insolvent firms) in a $q$ dimensions hyperspace. The lower the distance of $k$ from one centroid, the closer the borrower $k$ with that group, subject to the domain delimitated by the given $q$ variables profile.

The $q$ variables are obviously not independent to one another. They usually have interdependencies (correlation) that could duplicate meaningful information, biasing statistical estimates. To overcome this undesirable distortion, the Euclidean distance is transformed by taking these effects into consideration by the variables variance/covariance matrix. This criterion is the equivalent of using Mahalanobis' 'generalized distance' (indicated by $D$). The $k$ borrower attribution criterion becomes:

$$\min(D_k^2)=\min\left\{\left(x_k-\overline{x_{solv/insolv}}\right)'\times C^{-1}\times\left(x_k-\overline{x_{solv/insolv}}\right)\right\}$$

where $C$ is the $q$ variables variance/covariance matrix considered in model development. The minimization of the function can be reached by estimating the $Z$-score function as:

$$Z_k=\sum_{j=1}^{n}\beta_j x_{k,j}$$

in which $\beta=(\bar{X}_{insolv}-\bar{X}_{solv})'C^{-1}$.

In this last formula, $\bar{X}_{insolv}-\bar{X}_{solv}$ denotes the difference between the centroids of the two groups. In other words, the goal of LDA is to find the combination of variables that:

- maximizes the homogeneity around the two centroids;
- minimizes the overlapping zone in which the two groups of borrowers are mixed and share similar



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$Z$-scores; in this area the model is wrongly classifying observations which have uncertain profiles.

We can calculate the $Z$ values corresponding to the two centroids, respectively $\overline{Z_{solv}}$ and $\overline{Z_{insolv}}$, as the average $Z$ for each group. Subject to certain conditions, it can be proved that the optimal discriminant threshold (cut-off point) is given by:

$$Z_{cut-off} = \frac{\overline{Z_{solv}} - \overline{Z_{insolv}}}{2}$$

In order to assign the borrower to one of the two groups, it is sufficient to compare $Z_k$ of each $k$ observation to the set $Z_{cutoff}$. The sign and size of all $Z$ values are arbitrary; hence, the below/above threshold criterion could be reversed without any loss of generality and statistical meaning. Therefore, it is necessary to check each discriminant function one by one, to distinguish whether an increase in $Z$ indicates higher or lower risk.

Applying LDA to a sample, a certain number of firms will be correctly classified in their solvent/insolvent groups; inevitably, some observations will be incorrectly classified in the opposite group. The aim of LDA is to minimize this incorrect classification according to an optimization criterion defined in statistical terms.

The result is a number ($Z$), not standardized and dimensionally dependent from the variables used; it indicates the distance on a linear axis (in the $q$ variables hyperspace) between the two groups. The cut-off point is the optimal level of discrimination between the two groups; to simplify model's use and interpretation, sometimes it is set to zero by a very simple algebraic conversion.

Historically, these models were implemented to dichotomously distinguish between 'pass borrowers' (to grant loans to) and 'fail borrowers' (to avoid financing). Sometimes a gray area was considered, by placing two thresholds in order to have three ranges of $Z$-scores; the very safe borrowers, borrowers which need to be investigated further (possibly using credit analysts' expertise), and the very risky borrowers.

Today, we have two additional objectives: to assign ratings and to measure probability of default. These objectives are achieved by considering the score as an ascendant (descendant) grade of distance to the default, and categorizing scores in classes. This improvement does not yet satisfy the objective of obtaining a probability of default. To arrive at a probability measure, it is necessary to examine the concepts of model calibration and rating quantification.

LDA has some statistical requirements that should be met in order to avoid model inaccuracies and instability (Landau and Everitt, 2004; Giri, 2004; Stevens, 2002; Lyn, 2009), and are as follows:

1. independent variables are normally distributed;
2. absence of heteroscedasticity, that is, the matrix $C$ has to have similar values on the diagonal;
3. low independent variables multi-colinearity, that is, matrix $C$ has to have homogenous and preferably low values off the diagonal, not statistically significant;
4. homogeneous independent variables variance around groups' centroids, that is, matrix $C$ has to be (roughly) the same for firms in both solvent and insolvent groups.

The first three conditions can be overcome by adopting quadratic discriminant analysis instead of the linear discriminant analysis; in this case, we would use a model belonging to the group of Generalized Linear Models, which are discussed later when considering logistic regression models. The fourth condition is a real life constraint because, as a matter of fact, insolvent firms typically have more prominent variances (as they have more diversified profiles) than solvent ones.

### Model Calibration and the Cost of Errors

***Model calibration*** In statistics, there are many uses of the term calibration. In its broader meaning, calibration is any type of fitting empirical data by a statistical model. For the Basel Committee (2005a, page 3) calibration is the quantification of the probability of default. In a more specific use, it indicates procedures to determine class membership probabilities of a given new observation. Here, calibration is referred to as the process of determining default probabilities for populations, starting from statistical based rating systems' outputs and taking into account the difference between development samples' default rates and populations' default rates. In other words, once the scoring function has been estimated and $Z$-scores have been obtained, there are still some steps to undertake before the model can actually be used. It is necessary to distinguish between the two cases.

In the first case: the model's task is to accept or reject credit applications (or even having a gray area classification), but multiple rating classes and



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an estimate of probability of default per rating class are not needed. In this case, model calibration simply consists of adjusting the $Z$-score cut-off in order to take into account differences in default rates of samples and of population. This circumstance is typical of applications of credit scoring models to consumer loan applications or it is simply an intermediate step in analyzing and validating models' performance.

In the second case: the model's task is to classify borrowers in different rating classes and to assign probabilities of default to borrowers. In this case, model calibration includes, in addition to cut-off adjustment, all steps for quantifying default probabilities starting from $Z$-score and, if needed, for rescaling them in order to take into account differences in default rates of samples and of population.

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***Model calibration: Z-score cut-off adjustment*** In banks' loan portfolios, the number of defaulted firms is low compared to the number of non-defaulted firms. In randomly extracted samples, defaults are therefore very few in respects to performing firms. If this effect is not corrected when developing the model, the information on performing firms is overwhelming in comparison to the information on defaulted firms and, consequently, creates a bias in model estimation. In addition, LDA robustness suffers when variables have huge differences in their distribution in the two groups of borrowers. To limit these risks, the model building is carried out on more balanced samples, in which the two groups are more similar in size or, in extreme cases, have exactly the same sample size.

Therefore, when we apply model results to real populations, the risk is to over-predict defaults because, in the estimation sample, defaulted firms are overrepresented. In other words, the frequency of borrowers classified as defaulting by the model is higher than the actual default rate in the population and, as a consequence, we need to calibrate results obtained from the development sample.

If a model based on discriminant analysis has not yet been quantified in order to associate the probability of default to scores or rating classes, and it is only used to classify borrowers to the two groups of performing and defaulting firms, calibration only leads to change the $Z$ cut-off in order to achieve a frequency of borrowers classified as defaulting by the model equal to the default frequency in the actual population.

To calibrate a model based on discriminant analysis and used for classification purposes only, Bayes' theorem is applied. The theorem expresses the posterior probability (i.e., after evidence of scoring function variables values is observed) of a hypothesis (in our case, borrower's default), in terms of:

- the prior probabilities of the hypothesis, that is the probability of default when no evidence is collected on the specific borrower;
- the occurrence of evidence given the hypothesis, that is the probability of having a given $Z$-score in case the borrower defaults.

Consider that we have an $i$th borrower, described in its profile given by a variables vector $X$ and summarized by a $Z$-score. Prior probabilities are identified as $q$ and posterior probability as $p$. We can assume that:

- $q_{insolv}$ and $q_{solv}$ are the prior probabilities that the new $i$th observation will be attributed to the two groups without any regard to the information we have on them (the $X$ vector); in our case $(q_{insolv} + q_{solv}) = 1$. Let's suppose that the default rate in real world population is 2.38%. If we lend money to a generic firm, having no other information, we could rationally suppose that $q_{insolv}$ will be equal to 2.38% and $q_{solv}$ will be equal to $(1 - 2.38\%) = 97.62\%$.
- The conditional probabilities to attribute the $i$th new observation, described in its profile $X$, respectively to the defaulted and performing groups are $p_{insolv}(X|insolv)$ and $p_{solv}(X|solv)$; they are generated by the model using a given sample. Suppose we have a perfectly balanced sample and the firm $i$ is exactly on the cut-off point (hence the probability to be attributed to any of the two groups is 50%).

The simple probability (also called marginal probability) $p(X)$ can be written as the sum of joint probabilities:

$$p(X) = q_{insolv} \cdot p_{insolv}(X|insolv) + q_{solv} \cdot p_{solv}(X|solv)$$

$$p(X) = 2.38\% \times 50\% + 97.62\% \times 50\% = 50\%$$

It is the probability of having the $X$ profile of variables values (or its corresponding $Z$-score) in the considered sample, taking account of both defaulting and performing borrowers.

We are now in the position to use Bayes' theorem in order to adjust the cut-off by calibrating 'posterior probabilities'. The posterior probabilities, indicated by $p(insolv|X)$ and $p(solv|X)$, are the probabilities that, given the evidence



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of the $X$ variables, the firm $i$ belongs to the group of defaulted or non-defaulted firms in the population. Using Bayes' formula:

$$p(insolv|X) = \frac{q_{insolv} \cdot p_{insolv}(X|insolv)}{p(X)};$$
$$p(solv|X) = \frac{q_{solv} \cdot p_{solv}(X|solv)}{p(X)}$$

In our case, they will respectively be 2.38% and 97.62%.

In general, in order to calculate posterior probabilities, the framework in Table 4-9 can be used. Note that, in our case, the observation is located at the cut-off point of a balanced sample. Therefore, its conditional probability is 50%. When these circumstances are different, the conditional probabilities indicate in-the-sample probabilities of having a given value of $Z$-score for a solvent or insolvent firm. The sum of conditional probabilities is case specific and is not necessarily equal to 100%. The sum of joint probabilities represents the probability of having a given value of $Z$-score, considering both insolvent and solvent companies; again, this is a case specific value, depending on assumptions.

The new unit $i$ is assigned to the insolvent group if:

$$p(insolv/X) > p(solv/X)$$

Now consider firm $i$ having a $Z$-score exactly equal to the cut-off point (for a model developed using balanced samples). Its $Z$-score would be 2.38%; as it is far less than 97.62%, the firm $i$ has to be attributed to the performing group (and not to the group of defaulting firms). Therefore, the cut-off point has to be moved to take into consideration that the general population has a prior probability far less than we had in the sample.

To achieve a general formula, given Bayes' theorem and considering that $p(X)$ is present in both items of $p(insolv/X) > p(solv/X)$, the formulation becomes:

$$q_{insolv} \cdot p_{insolv}(X/insolv) > q_{solv} \cdot p_{solv}(X/solv)$$

Hence, the relationship can be rewritten as:

$$\frac{p_{insolv}(X|insolv)}{p_{solv}(X|solv)} > \frac{q_{solv}}{q_{insolv}}$$

This formulation gives us the base to calibrate the correction to the cut-off point to tune results to the real world.

One of the LDA pre-requisites is that the distributions of the two groups are normal and similar. Given these conditions, Fisher's optimal solution for the cut-off point (obtained when *prior* chances to be attributed to any group is 50%) has to be relocated by the relation $\left[\ln\frac{q_{solv}}{q_{insolv}}\right]$. When the prior probabilities $q_{insolv}$ and $q_{solv}$ are equal (balanced sample), the relation is equal to zero, that is to say that no correction is needed to the cut-off point. If the population is not balanced, the cut-off point has to be moved by adding an amount given by the above relation to the original cut-off.

A numerical example can help. Assume we have a $Z$-score function, estimated using a perfectly balanced sample, and having a cut-off point at zero (for our convenience). As before, also assume that the total firms' population is made by all Italian borrowers (including non-financial corporations, family concerns, and small business) as recorded by the Italian Bank of Italy's Credit Register. During the last 30 years, the average default rate of this population (the a priori probability $q_{insolv}$) is 2.38%; the opposite (complement to one) is therefore 97.62% ($q_{solv}$,

**TABLE 4-9** Bayes' Theorem Calculations

| Event | Prior Probabilities (%) | Conditional Probabilities of the *i*th Observation (%) | Joint Probabilities and Their Sum (%) | Posterior Probabilities of the *i*th Observation (%) |
|---|---|---|---|---|
| Default | $q_{insolv} = 2.38$ | $p_{insolv}(X\|insolv) = 50$ | $q_{insolv} \cdot p_{insolv}(X\|insolv) = 1.19$ | $p(insolv\|X) = 2.38$ |
| Non-default | $q_{solv} = 97.62$ | $p_{solv}(X\|solv) = 50$ | $q_{solv} \cdot p_{solv}(X/solv) = 48.81$ | $p(solv\|X) = 97.62$ |
| Sum | 100 | — | $P(X) = 50$ | 100 |



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in our notation). The quantity to be added to the original $Z$-score cut-off is consequently:

$$\ln\frac{97.62\%}{2.38\%} = 3.71$$

The proportion of defaulted firms on the total population is called 'central tendency', a value that is of paramount importance in default probability estimation and in real life applications.

***Cost of misclassification*** A further important aspect is related to misclassifications and the cost of errors. No model is perfect when splitting the two groups of performing and defaulting firms. Hence, there will be borrowers that:

- are classified as potentially defaulted and would be rejected despite the fact that they will be solvent, therefore leading to the loss of business opportunities;
- are classified as potentially solvent and will be granted credit, but they will fall into default generating credit losses.

It is evident that the two types of errors are not equally costly when considering the potential loss arising from them. In the first case, the associated cost is an opportunity cost (regarding business lost, and usually calculated as the discounted net interest margin and fees not earned on rejected transactions), whereas the second case corresponds to the so-called loss given default examined in Chapter 3. For such reasons, it may be suitable to correct the cut-off point in order to take these different costs into consideration. Consider:

- $COST_{insolv/solv}$ the cost of false-performing firms that, once accepted, generate defaults and credit losses,
- $COST_{solv/insolv}$ the cost of false-defaulting firms, whose credit application rejection generate losses in business opportunities,

and assume that (hypothetically) $COST_{insolv/solv} = 60\%$ (current assessment of LGD) and $COST_{solv/insolv} = 15\%$ (net discounted values of business opportunities). The optimal cut-off point solution changes as follows:

$$\frac{p_{insolv}(X)}{p_{solv}(X)} > \frac{q_{solv} \times COST_{solv/insolv}}{q_{insolv} \times COST_{insolv/solv}}$$

Then, we have to add to the original cut-off an amount given by the relation $\left[\ln\frac{q_{solv} \times COST_{solv/insolv}}{q_{insolv} \times COST_{insolv/solv}}\right]$. Coming back to the previous example, by adding a weighted cost criterion, the cut-off point will be converted as follows:

$$\ln\frac{97.61\% \times 15\%}{2.38\% \times 60\%} = 2.33$$

This will be added to the original cut-off point to select new borrowers in pass/reject approaches, taking into consideration the cost of misclassification and the central default tendency of the population.

As a matter of fact, the sensitivity of the cut-off to the main variables (population default rate, misclassification costs and so forth) is very high. Moreover, moving the cut-off, the number rejected/accepted will generally change very intensively, determining different risk profiles of the credit portfolio originating from this choice. Cut-off relevance is so high that the responsibility to set *pro tempore* cut-offs is in the hand of offices different from those devoted to model building and credit analysis, and involves marketing and (often) planning departments. The cut-off point selection is driven by market trends, competitive position on various customer segments, past performances and budgets, overall credit portfolio profile, market risk environment (interest rates time structure, risk premium, capital market opportunities), funding costs and so forth in a holistic approach.

### *From Discriminant Scores to Default Probabilities*

LDA has the main function of giving a taxonomic classification of credit quality, given a set of pre-defined variables, splitting borrowers' transactions in potentially performing/defaulting firms. The typical decisions supported by LDA models are accept/reject ones.

Modern internal rating systems need something more than a binary decision, as they are based on the concept of default probability. So, if we want to use LDA techniques in this environment, we have to work out a probability, not only a classification in performing and defaulting firms' groups. We have to remember that a scoring function is not a probability but a distance expressed like a number (such as Euclidean distance, geometric distance—as the 'Mahalanobis distance' presented earlier—and so forth) that has a meaning in a domain of $n$ dimensions hyperspace given by independent variables that describe borrowers to be classified. Therefore, when a LDA model's task is to classify borrowers in different rating classes and to assign probabilities of default to borrowers, model calibration includes, in addition to cut-off adjustment, all steps for quantifying default probabilities starting from



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Z-score and, if needed, for rescaling them in order to take into account differences in default rates of samples and of population.

The probability associated to the scoring function can be determined by adopting two main approaches: the first being empirical, the second analytical. The empirical approach is based on the observation of default rates associated to ascendant cumulative discrete percentiles of Z-scores in the sample. If the sample is large enough, a lot of scores are observed for defaulted and non-defaulted companies. We can then divide this distribution in discrete intervals. By calculating the default rate for each class of $Z$ intervals, we can perceive the relationship between $Z$ and default frequencies, which are our a priori probabilities of default. If the model is accurate and robust enough, default frequency is expected to move monotonically with $Z$ values. Once the relationship between $Z$ and default frequencies is set, we can infer that this relation will also hold in the future, extending these findings to new (out-of-sample) borrowers. Obviously, this correspondence has to be continuously monitored by periodic back testing to assess if the assumption is still holding.

The analytical approach is based again on the application of Bayes' theorem. Z-scores have no inferior or superior limits whereas probabilities range between zero and one. Let's denote again with $p$ the posterior probabilities and with $q$ the priors probabilities. Bayes' theorem states that:

$$p(insolv|X) = \frac{q_{insolv} \times p_{insolv}(X|insolv)}{q_{insolv} \times p_{insolv}(X|insolv) + q_{solv} \times p_{solv}(X|solv)}$$

The general function we want to achieve is a logistic function such as:

$$p(insolv|X) = \frac{1}{e^{\alpha+\beta X}}$$

It has the desired properties we are looking for: it ranges between zero and one and depends on $Z$-scores estimated by discriminant analysis.

In fact, it is possible to prove that, starting from the discriminant function $Z$, we obtain the above mentioned logistic expression by calculating:

$$\begin{aligned}\alpha &= \ln\left(\frac{q_{solv}}{q_{insolv}}\right) - \frac{1}{2}(\overline{x_{solv}} - \overline{x_{insolv}})'C^{-1}(\overline{x_{solv}} - \overline{x_{insolv}}) \\ &= \ln\left(\frac{q_{solv}}{q_{insolv}}\right) - Z_{cut\text{-}off} \\ \beta &= C^{-1}(\overline{x_{solv}} - \overline{x_{insolv}})\end{aligned}$$

As previously mentioned, $C$ is the variance/covariance matrix, and $x$ are the vectors containing means of the two groups (defaulted and performing) in the set of variables $X$. Therefore, logistic transformation can be written as:

$$p(insolv|X) = \frac{1}{e^{\ln\left(\frac{q_{solv}}{q_{insolv}}\right) - Z_{cut\text{-}off} + Z_i}}$$

in which $Z_{cut\text{-}off}$ is the cut-off point before calibration and $p(insolv|X)$ is the calibrated probability of default.

Once this calibration has been achieved, a calibration concerning cost misclassifications can also be applied.

## Statistical Methods: Logistic Regression

Logistic regression models (or LOGIT models) are a second group of statistical tools used to predict default. They are based on the analysis of dependency among variables. They belong to the family of Generalized Linear Models (GLMs), which are statistical models that represent an extension of classical linear models; both these families of models are used to analyze dependence, on average, of one or more dependent variables from one or more independent variables. GLMs are known as generalized because some fundamental statistical requirements of classical linear models, such as linear relations among independent and dependent variables or the constant variance of errors (homoscedasticity hypothesis), are relaxed. As such, GLMs allow modeling problems that would otherwise be impossible to manage by classical linear models.

A common characteristic of GLMs is the simultaneous presence of three elements:

1. *A Random Component:* identifies the target variable and its probability function.
2. *A Systematic Component:* specifies explanatory variables used in a linear predictor function.
3. *A Link Function:* a function of the mean of the target variable that the model equates to the systematic component.

These three elements characterize linear regression models and are particularly useful when default risk is modeled.

Consider a random binary variable, which takes the value of one when a given event occurs (the borrower defaults), and otherwise it takes a value of zero. Define $\pi$ as the



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probability that this event takes place; $Y$ is a Bernoulli distribution with known characteristics ($Y \sim \text{Ber}(\pi)$, with $\pi$ being the unknown parameter of the distribution). $Y$, as a Bernoullian distribution, has the following properties:

- $P(Y = 1) = \pi$, $P(Y = 0) = 1 - \pi$
- $E(Y) = \pi$, $Variance(Y) = \pi(1 - \pi)$
- $f(y : \pi) = \pi^y(1 - \pi)^{1-y}$ *per* $y \in \{0, 1\}$ *e* $0 \leq \pi \leq 1$

Therefore, $Y$ is the random component of the model.

Now, consider a set of $p$ variables $x_1, x_2, \ldots, x_p$ (with $p$ lower than the number $n$ of observations), $p + 1$ coefficients $\beta_0, \beta_1, \ldots, \beta_p$ and a function $g(\cdot)$. This function is known as the 'link function', which links variables $x_j$ and their coefficients $\beta_j$ with the expected value $E(Y_i) = \pi_i$ of the $i$th observation of $Y$, using a linear combination such as:

$$g(\pi_i) = \beta_0 + \beta_1 \cdot x_{i1} + \beta_2 \cdot x_{i2}, \ldots, + \beta_p \cdot x_{ip} = \beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij} \quad i = 1, \ldots, n$$

This linear combination is known as a linear predictor of the model and is the systematic component of the model.

The link function $g(\pi_i)$ is monotonic and differentiable. It is possible to prove that it links the expected value of the dependent variable (the probability of default) with the systematic component of the model which consists of a linear combination of the explicative variables $x_1, x_2, \ldots, x_p$ and their effects $\beta_i$.

These effects are unknown and must be estimated. When a Bernoullian dependent variable is considered, it is possible to prove that:

$$g(\pi_i) = \log\frac{\pi_i}{1 - \pi_i} = \beta_0 + \sum_{j=1}^{p} \beta_j \cdot x_{ij} \qquad i = 1, \ldots, n$$

As a consequence, the link function is defined as the logarithm of the ratio between the probability of default and the probability of remaining a performing borrower. This ratio is known as 'odds' and, in this case, the link function $g(\cdot)$ is known as LOGIT (to say the logarithm of *odds)*:

$$\text{logit}(\pi_i) = \log\frac{\pi_i}{1 - \pi_i}$$

The relation between the odds and the probability of default can be written as: $odds = \pi/(1 - \pi)$ or, alternatively, as $\pi = odds/(1 + odds)$.

Therefore, a LOGIT function associates the expected value of the dependent variable to a linear combination of the independent variables, which do not have any restrictive hypotheses. As a consequence, any type of explanatory variables is accepted (both quantitative and qualitative, and both scale and categorical), with no constraints concerning their distribution. The relationship between independent variables and the probability of default $\pi$ is nonlinear (whereas the relation between logit ($\pi$) and independent variables is linear). To focus differences with the classical linear regression, consider that:

- In classical linear regression the dependent variable range is not limited and, therefore, may assume values outside the [0; 1] interval; when dealing with risk, this would be meaningless. Instead, a logarithmic relation has a dependent variable constrained between zero and one.
- The hypothesis of homoscedasticity of the classical linear model is meaningless in the case of a dichotomous dependent variable because, in this circumstance, variance is equal to $\pi$ ($1 - \pi$).
- The hypothesis testing of regression parameters is based on the assumptions that errors in prediction of the dependent variables are distributed similarly to normal curves. But, when the dependent variable only assumes values equal to zero or one, this assumption does not hold.

It is possible to prove that logit ($\pi$) can be rewritten in terms of default probability as:

$$\pi_i = \frac{1}{1 + e^{-\left(\beta_0 + \sum_{j=1}^{p} \beta_j x_{ij}\right)}} \qquad i = 1, \ldots, n$$

When there is only one explanatory variable $x$, the function can be graphically illustrated, as in Figure 4-5.

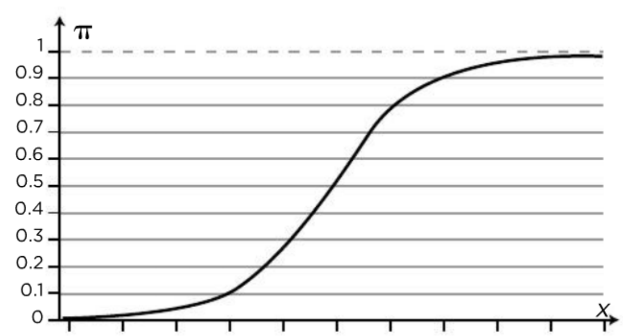


**FIGURE 4-5** Default probability in the case of a single independent variable.



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Note that this function is limited within the [0;1] interval, and is coherent with what we expect when examining a Bernoullian dependent variable: in this case, the coefficient $\beta_i$ sets the growth rate (negative or positive) of the curve and, if it is negative, the curve would decrease from one to zero; when $\beta$ has a tendency towards zero, the curve flattens, and for $\beta = 0$ the dependent variable would be independent from the explanatory variable.

Now, let's clarify the meaning of 'odds'. As previously mentioned, they are the ratio between default probability and non-default probability.

Continuing to consider the case of having only one explanatory variable, the LOGIT function can be rewritten as:

$$\frac{\pi_i}{1-\pi_i} = e^{(\beta_0+\beta_1 x_{i1})} = e^{\beta_0} \cdot \left(e^{\beta_1}\right)^{x_{i1}}$$

It is easy to interpret $\beta$. The odds are increased by a multiplicative factor $e^{\beta}$ for one unit increase in $x$; in other words, odds for $x + 1$ equal odds for $x$ multiplied by $e^{\beta}$. When $\beta = 0$, then $e^{\beta} = 1$ and thus odds do not change when $x$ assumes different values, confirming what we have just mentioned regarding the case of independency. Therefore:

$$e^{\beta} = \frac{\text{odds after a unit change in the predictor}}{\text{original odds}}$$

We call this expression 'odds ratio'. Be cautious because the terminology used for odds is particularly confusing: often, the term that is used for odds is 'odds ratios' (and consequently this ratio should be defined as 'odds ratio ratio'!).

In logistic regression, coefficients are estimated by using the 'maximum likelihood estimation' (MLE) method; it selects the values of the model parameters that make data more likely than any other parameter' values would.

If the number of observations $n$ is high enough, it is possible to derive asymptotic confidence intervals and hypothesis testing for the parameters. There are three methods to test the null hypothesis $H_0 : \beta_i = 0$ (indicating, as mentioned previously, that the probability of default is independent from explanatory variables). The most used method is the Wald statistic.

A final point needs to be clarified. Unlike LDA, logistic regression already yields sample-based estimates of the probability of default (PD), but this probability needs to be rescaled to the population's prior probability. Rescaling default probabilities is necessary when the proportion of bad borrowers in the sample 'is different from the actual composition of the portfolio (population) in which the logistic model has to be applied. The process of rescaling the results of logistic regression involves six steps (OeNB and FMA, 2004):

1. Calculation of the average default rate resulting from logistic regression using the development sample ($\pi$);
2. Conversion of this sample's average default rate into sample's average odds (SampleOdds), and calculated as follows:

$$Odds = \frac{\pi}{1-\pi}$$

3. Calculation of the population's average default rate (prior probability of default) and conversion into population average odds (PopOdds);
4. Calculation of unscaled odds from default probability resulting from logistic regression for each borrower;
5. Multiplication of unscaled odds by the sample-specific scaling factor:

$$ScaledOdds = UnscaledOdds \cdot \frac{PopOdds}{SampleOdds}$$

6. Conversion of the resulting scaled odds into scaled default probabilities ($\pi_S$):

$$\pi_S = \frac{ScaledOdds}{1 + ScaledOdds}$$

This makes it possible to calculate a scaled default probability for each possible value resulting from logistic regression. Once these default probabilities have been assigned to grades in the rating scale, the calibration is complete.

It is important to assess the calibration of this prior-adjusted model. The population is stratified into quantiles, and the log odds mean is plotted against the log of default over performing rates in each quantile. In order to better reflect the population, default and performing rates are reweighted as described above for the population's prior probability. These weights are then used to create strata with equal total weights, and in calculating the mean odds and ratio of defaulting to performing. The population is divided among the maximum number of quantiles so that each contains at least one defaulting or performing case and so that the log odds are finite. For a



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perfectly calibrated model, the weighted mean predicted odds would equal the observed weighted odds for all strata, so the points would lie alongside the diagonal.

## From Partial Ratings Modules to the Integrated Model

Statistical models' independent variables may represent variegate types of information:

1. firms' financial reports, summarized both by ratios and amounts;
2. internal behavioral information, produced by operations and payments conveyed through the bank or deriving from periodical accounts balances, facility utilizations, and so on;
3. external behavioral information, such as credit bureau reports, formal and informal notification about payments in arrears, dun letters, legal disputes and so on;
4. credit register's behavioral data, summarizing a borrower's credit relationships with all reporting domestic banks financing it;
5. qualitative assessments concerning firms' competitiveness, quality of management, judgments on strategies, plans, budgets, financial policies, supplier and customer relationships and so forth.

These sources of information are very different in many aspects: frequency, formalization, consistency, objectivity, statistical properties, and data type (scale, ordinal, nominal). Therefore, specific models are often built to separately manage each of these sources. These models are called 'modules' and produce specific scores based on the considered variables; they are then integrated into a final rating model, which is a 'second level model' that uses the modules' results as inputs to generate the final score. Each model represents a partial contribution to the identification of potential future defaults.

The advantages of using modules, rather than building a unitary one-level model, are:

- To facilitate models' usage and maintenance, separating modules using more dynamic data from modules which use more stable data. Internal behavioral data are the most dynamic (usually they are collected on a daily basis) and sensitive to the state of the economy, whereas qualitative information is seen as the steadiest because the firm's qualitative profile changes slowly, unless extraordinary events occur.
- To re-calculate only modules for which new data are available.
- To obtain a clear picture of the customer's profiles which are split into different analytical areas. Credit officers are facilitated to better understand the motivations and weaknesses of a firm's credit quality profile. At the same time, they can better assess the coherence and suitability of commercial proposals.
- All different areas of information contribute to the final rating; in one-level models the entire set of variables belonging to a specific area can be crowded out by other more powerful indicators.
- When a source of information is structurally unavailable (for instance, internal behavioral data for a prospective bank customer), different second-level models can be built by only using the available module, in order to tackle these circumstances.
- Information in each module has its peculiar statistical properties and, as a consequence, model building can be conveniently specialized.

Modules can be subsequently connected in parallel or in sequence, and some of them can be model based or rather judgment based. Figure 4-6 illustrates two possible solutions for the model structure. In Solution A (parallel approach), modules' outputs are the input for the final second-level rating model. In the example in Figure 4-6, judgment-based analysis is only added at the end of the process involving model-based modules; in other cases, judgment-based analysis can contribute to the final rating in parallel with other modules, as one of the modules which produces partial ratings. In Solution B there is an example of sequential approach (also known as the 'notching up/down approach'). Here, only financial information feeds the model whereas other modules notch financial model results up/down, by adopting structured approaches (notching tables or functions) or by involving experts into the notching process.

When modules are used in parallel, estimating the best function in order to consolidate them in a final rating model is not a simple task. On one hand, outputs from different datasets explain the same dependent variables; inevitably, these outputs are correlated to each other and may lead to unstable and unreliable final results; specific tests have to be performed (such as the Durbin-Watson test). On the other hand, there are many possible methodological alternatives to be tested

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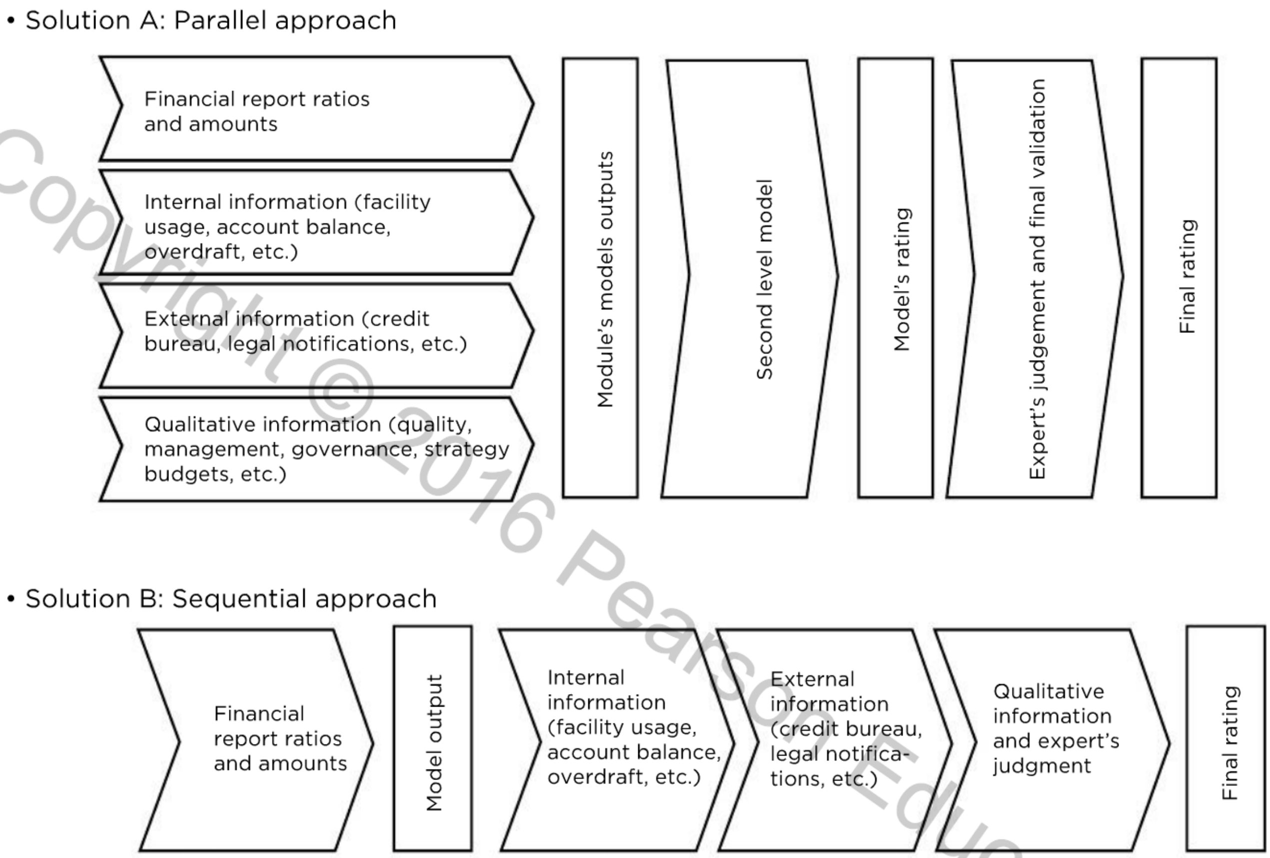


**FIGURE 4-6** Possible architectures to structure rating modules in final rating.

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and important business considerations to be taken into account.

## Unsupervised Techniques for Variance Reduction and Variables' Association

Statistical approaches such as LDA and LOGIT methods are called 'supervised' because a dependent variable is defined (the default) and other independent variables are used to work out a reliable solution to give an *ex ante* prediction. Hereafter, we will illustrate other statistical techniques, defined as 'unsupervised' because a dependent variable is not explicitly defined. The borrowers or variables' sets are reduced, through simplifications and associations, in an optimal way, in order to obtain some sought-after features. Therefore, these statistical techniques are not directly aimed at forecasting potential defaults of borrowers but are useful in order to simplify available information. In particular, unsupervised statistical techniques are very useful for segmenting portfolios and for preliminary statistical explorations of borrowers' characteristics and variables' properties.

Given a database with observations in rows and variables in columns:

- 'Cluster analysis' operates in rows aggregating borrowers on the basis of their variables' profile. It leads to a sort of statistically-based top down segmentation of borrowers. Subsequently, the empirical default rate, calculated segment by segment, can be interpreted as the borrower' default probability of each segment. Cluster analysis can also be simply used as a preliminary exploration of borrowers characteristics.
- 'Principal component analysis', 'factor analysis', and 'canonical correlation analysis' all operate in columns in order to optimally transform the set of variables into a smaller one, which is statistically more significant.



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In the future, these techniques may have a growing importance in order to build 'second generation' models in which the efficient use of information is essential.

### *Cluster Analysis*

The objective of cluster analysis is to explore if, in a dataset, groups of similar cases are observable. This classification is based on 'measures of distance' of observations' characteristics. Clusters of observations can be discovered using an aggregating criterion based on a specific homogeneity definition. Therefore, groups are subsets of observations that, in the statistical domain of the $q$ variables, have some similarities due to analogous variables' profiles and are distinguishable from those belonging to other groups. The usefulness of clusters depends on:

- algorithms used to define them,
- economic meanings that we can find in the extracted aggregations.

Operationally, we can use two approaches: hierarchical or aggregative on the one hand, and partitioned or divisive on the other hand (Tan, Steinbach, and Kumar, 2006).

***Hierarchical clustering*** Hierarchical clustering creates a hierarchy of clusters, aggregating them on a case-by-case basis, to form a tree structure (often called *dendrogram),* with the leaves being clusters and the roots being the whole population. Algorithms for hierarchical clustering are generally agglomerative, in the sense that we start from the leaves and successively we merge clusters together, following branches till the roots. Given the choice of the linkage criterion, the pair-wise distances between observations are calculated by generating a table of distances. Then, the nearest cases are aggregated and each resulting aggregation is considered as a new unit. The process re-starts again, generating new aggregations, and so on until we reach the root. Cutting the tree at a given height determines the number and the size of clusters; often, a graph presentation is produced in order to immediately visualize the most convenient decision to make. Usually, the analysis produces:

- a small number of large clusters with high homogeneity,
- some small clusters with well defined and comprehensible specificities,
- single units not aggregated with others because of their high specificity.

Such a vision of data is of paramount importance for subsequent analytical activities, suggesting for instance to split groups that would be better analyzed by different models.

As mentioned before, the choice of the distance measure to use is crucial in order to have meaningful final results. The measures which are most used are:

- the Euclidean distance,
- the geometric distance (also called Mahalanobis distance), which takes into account different scales of data and correlations in the variables,
- the Hamming distance, which measures the minimum number of substitutions required to change one case into another,
- some homogeneity measures, such as the $\chi^2$ test and the Fisher's F test.

Obviously, each criterion has its advantages and disadvantages. It is advisable to pre-treat variables in order to reach a similar magnitude and variability; indeed, many methods are highly influenced by variables' dimension and variance, and, thus, in order to avoid being unconsciously driven by some specific population feature, a preliminary transformation is highly recommended.

This method has many applications. One is the anomalies' detection; in the real world, many borrowers are outliers, that is to say, they have a very high specificity. In a bank's credit portfolio, start-ups, companies in liquidation procedures, and companies which have just merged or demerged, may have very different characteristics from other borrowers; in other cases, abnormalities could be a result of missing data and mistakes. Considering these cases while building models signifies biasing model coefficients estimates, diverting them from their central tendency. Cluster analysis offers a way to objectively identify these cases and to manage them separately from the remaining observations.

***Divisive clustering*** The partitional (or divisive) approach is the opposite of hierarchical clustering, because it starts at the root and recursively splits clusters by algorithms that assign each observation to the cluster whose center (also called centroid) is the nearest. The center is the average of all the points in the cluster. According to this approach, the number of clusters ($k$) is chosen exogenously using some rules. Then, $k$ randomly generated clusters are determined with their cluster center. Each observation is assigned to the cluster whose center is the nearest; new cluster centers are re-calculated and the procedure is



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repeated until some convergence criterion is met. A typical criterion is that the cases assignment has not changed from one round to the next. At the end of the analysis a min–max solution is reached: the intra-group variance is minimized and the inter-group variance is maximized (subject to the constraint of the chosen clusters' number). Finally, the groups' profile is obtained showing the centroid and the variability around it. Some criteria help to avoid redundant iterations, avoiding useless or inefficient algorithm rounds.

The interpretation is the same for hierarchical methods: some groups are homogeneous and numerous while others are much less so, with other groups being typically residual with a small number of observations that are highly spread in the hyperspace which is defined by variables set. Compared to aggregative clustering, this approach could appear better as it tends to force our population in fewer groups, often aggregating hundreds of observations into some tens of clusters.

The disadvantage of these approaches is the required high calculation power. It exponentially increases with the number of initial observations and the number of iterative rounds of the algorithm. For such reasons, divisive applications are often limited to preliminary explorative analyses.

### *Principal Component Analysis and Other Similar Methodologies*

Let's return to our data table containing $n$ cases described by $q$ variables $X$. Using cluster analysis techniques we have dealt with the table by rows (cases). Now, we will examine the possibility to work on columns (variables). These modifications are aimed at substituting the $q$ variables in a smaller (far smaller) number of new $m$ variables, which are able to summarize the majority of the original total variance measured in the given $q$ variables profiles. Moreover, this new $m$ set that we will obtain has more desirable features, like orthogonality, less statistical 'noise' and analytical problems. Therefore, we can reach an efficient description, reducing the number of variables, linearly independent from each other.

Far beyond this perspective, these methods tend to unveil the database 'latent structure'. The assumption is that much of the phenomena are not immediately evident. In reality, the variables we identify and measure are only a part of the potential evidence of a complex, underlying phenomenon. A typical example is offered in the definition of intelligence in psychology. It is impossible to directly measure intelligence *per se;* the only method we have is to sum up the partial measures related to the different manifestations of intelligence in real life. Coming back to finance, for instance, firm profitability is something that is apparent at the conceptual level but, in reality, is only a composite measure (ROS, ROI, ROE, and so forth); nevertheless, we use the profitability concept as a mean to describe the probability of default; so we need good measures, possibly only one.

What can we do to reach this objective? The task is not only to identify some aspects of the firm's financial profile but also to define how many 'latent variables' are behind the ratio system. In other words, how much basic information do we have in a balance sheet that is useful for developing powerful models, avoiding redundancy but maintaining a sufficient comprehensiveness in describing the real circumstances?

Let's describe the first of these methods; one of the most well known is represented by 'principal components analysis'. With this statistical method, we aim to determine a transformation of the original $n \times q$ table into a second, derived, table $n \times w$, in which, for the generic $j$ case (described through $x_j$ in $q$ original variables) the following relation holds:

$$w_j = Xa_j$$

subject to the following conditions:

1. Each $w_i$ summarizes the maximum residual variance of the original $q$ variables which are left unexplained by the $(i - 1)$ previously extracted principal component. Obviously, the first one is the most general among all $w$ extracted.
2. Each $w_i$ is perpendicular in respect to the others.

Regarding 1, we must introduce the concept of principal component communality. As mentioned before, each $w$ has the property to summarize part of the variance of the original $q$ variables. This performance (variance explained divided by total original variance) is called communality, and is expressed by the $w_i$ principal component. The more general the component is (i.e., has high communality) the more relevant is the ability to summarize the original variables set in one new composed variable. This would compact information otherwise decomposed in many different features, measured by a plethora of figures.

Determination of the principal components is carried out by recursive algorithms. The method is begun by extracting the first component that reaches the maximum communality; then, the second is extracted by operating on

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the residuals which were not explained by the previous component, under the constraint of being orthogonal, until the entire original variables set is transformed into a new principal components set.

Doing this, because we are recursively trying to summarize as much as we can of the original total variance, the component that are extracted later contribute less to explain the original variables set. Starting from the first round, we could go on until we reach:

- a minimum pre-defined level of variance that we want to explain using the subset of new principal components,
- a minimum communality that assures us that we are compacting enough information when using the new component set, instead of the original variables set.

From a mathematical point of view, it is proven that the best first component is corresponding to the first eigenvalue (and associated eigenvector) of the variables set; the second corresponds to the first eigenvalue (and associated eigenvector) extracted on the residuals, and so on. The eigenvalue is also a measure of the corresponding communality associated to the extracted component. With this in mind, we can achieve a direct and easy rule. If the eigenvalue is more than one, we are sure that we are summarizing a part of the total variance that is more than the information given by an individual original variable (all the original variables, standardized, have contribution of one to the final variance). Conversely, if the eigenvalue is less than one, we are using a component that contributes less than an original variable to describe the original variability. Given this rule, a common practice is to only consider the principal component that has an eigenvalue of more than one.

If some original variables are not explained enough by the new principal component set, an iterative process can be performed. These variables are set apart from the database and a new principal component exercise is carried out until what could be summarized is compacted in the new principal component set and the remaining variables are used as they are. In this way, we can arrive at a very small number of features, some given by the new, orthogonally combined variables (principal components) and others by original ones.

Let's give an example to better understand these analytical opportunities. We can use results from a survey conducted in Italy on 52 firms based in northern Italy, which operate in the textile sector (Grassini, 2007). The goal of the survey was to find some aspects of sector competition; the variables refer to profitability performances, financial structure, liquidity, leverage, the firms positioning in the product/segment, R&D intensity, technological profile, and marketing organization. The variables list is shown in Table 4-10.

Table 4-11 shows the results of principal components extracted, that is to say, the transformation of the original variables set in another set with desirable statistical features. The new variables (components) are orthogonal and (as in a waterfall) explain the original variance in descending order.

The first three components summarize around 81% of the total original variance, and eigenvalues explain how much variance is accounted by each component. The first component, despite being the most effective, takes into account 40% of the total. Therefore, a model based only on one component does not account for more than this and would be too inefficient. By adding two other features (represented by the other two components), we can obtain a picture of four-fifths of the total variability, which can be considered as a good success. Table 4-12 shows the correlation coefficients between the original variables set and the first three components. This table is essential for detecting the meaning of the new variables (components) and, therefore, to understand them carefully.

The first component is the feature that characterizes the variables set the most. In this case, we can see that it is highly characterized by the liquidity variables, either directly (for current liquidity and quick liquidity ratios) or inversely correlated (financial leverage). A good liquidity structure reduces leverage and vice versa; so the sign and size of the relationships are as expected. There are minor (but not marginal) effects on operational and shareholders' profitability: that is, liquidity also contributes to boost firm's performances; this relationship is also supported by results of the Harvard Business School's Profit Impact of Market Strategy (PIMS) database long term analysis (Buzzell and Gale, 1987, 2004).

The second component focuses on profitability. The lighter the capital intensity of production, the better the generated results are, particularly in respect of working capital requirements.

The third component summarizes the effects of intangibles, market share and R&D investments. In fact, R&D and intangibles are related to the firm's market share, that is to say, to the firm's size. What is worth noting is that the principal components' pattern does not justify the perception of a relation between intangibles, market share and profitability and/or liquidity.



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**TABLE 4-10** Variables, Statistical Profile and Correlation Matrix

| Variables Typology | Variable Denomination | Definition |
|---|---|---|
| Profitability performance | ROE | net profit/net shareholders capital |
| | ROI | EBIT/invested capital |
| | SHARE | market share (in %) |
| Financial structure on short and medium term horizon | CR | current assets/current liabilities |
| | QR | liquidity/current liabilities |
| | MTCI | (current liabilities + permanent liabilities)/invested capital |
| Intangibles (royalties, R&D expenses, product development and marketing) | R&S | intangibles fixed assets/invested capital (in percentage) |

| Ratios | Mean | Minimum Value | Maximum Value | Standard Deviation | Variability Coefficient | Asymmetry | Kurtosis |
|---|---|---|---|---|---|---|---|
| ROE | 0.067 | −0.279 | 0.688 | 0.174 | 2.595 | 1.649 | 5.088 |
| ROI | 0.076 | −0.012 | 0.412 | 0.078 | 1.024 | 2.240 | 5.985 |
| CR | 1.309 | 0.685 | 3.212 | 0.495 | 0.378 | 1.959 | 4.564 |
| QR | 0.884 | 0.169 | 2.256 | 0.409 | 0.463 | 1.597 | 2.896 |
| MTCI | 0.787 | 0.360 | 1.034 | 0.151 | 0.192 | −0.976 | 0.724 |
| SHARE (%) | 0.903 | 0.016 | 6.235 | 1.258 | 1.393 | 2.594 | 7.076 |
| R&S (%) | 0.883 | 0.004 | 6.120 | 1.128 | 1.277 | 2.756 | 9.625 |

| Ratios | ROE | ROI | CR | QR | MTCI | SHARE (%) | R&S (%) |
|---|---|---|---|---|---|---|---|
| ROE | 1.000 | | | | | | |
| ROI | **0.830** | 1.000 | | | | | |
| CR | -0.002 | 0.068 | 1.000 | | | | |
| QR | 0.034 | 0.193 | **0.871** | 1.000 | | | |
| MTCI | −0.181 | −0.333 | **−0.782** | **−0.749** | 1.000 | | |
| SHARE (%) | 0.086 | 0.117 | −0.128 | −0.059 | 0.002 | 1.000 | |
| R&S (%) | −0.265 | −0.144 | −0.155 | −0.094 | −0.013 | 0.086 | 1.000 |

Bold: statistically meaningful correlation.

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**TABLE 4-11** Principal Components

| Components | Eigenvalues | Explained Variance on Total Variance (%) | Cumulated Variance Explained (%) |
|---|---|---|---|
| COMP1 | 2.762 | 39.458 | 39.458 |
| COMP2 | 1.827 | 26.098 | 65.556 |
| COMP3 | 1.098 | 15.689 | 81.245 |
| COMP4 | 0.835 | 11.922 | 93.167 |
| COMP5 | 0.226 | 3.226 | 96.393 |
| COMP6 | 0.172 | 2.453 | 98.846 |
| COMP7 | 0.081 | 1.154 | 100.000 |
| **Total** | 7.000 | 100.000 | |

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**TABLE 4-12** Correlation Coefficients between Original Variables and Components

| Ratios | COMP1 | COMP2 | COMP3 | $R^2$(Communalities) | Singularity* |
|---|---|---|---|---|---|
| ROE | 0.367 | **0.875** | 0.053 | 0.902 | 0.098 |
| ROI | 0.486 | **0.798** | −0.100 | 0.883 | 0.117 |
| CR | **0.874** | −0.395 | 0.057 | 0.923 | 0.077 |
| QR | **0.885** | −0.314 | −0.044 | 0.883 | 0.117 |
| MTCI | **−0.892** | 0.149 | 0.196 | 0.856 | 0.144 |
| SHARE (%) | −0.055 | 0.259 | **−0.734** | 0.609 | 0.391 |
| R&S (%) | −0.215 | −0.286 | **−0.709** | 0.631 | 0.369 |

*Share of variable's variance left unexplained by the considered components.

The picture that is achieved by the above exercise is that, in the textile sector in Northern Italy, the firm's profile can be obtained by a random composition of three main components. That is to say, a company could be liquid, not necessarily profitable and with high investments in intangibles, with a meaningful market share. Another company could be profiled in a completely different combination of the three components.

Given the pattern of the three components, a generic new firm *j*, belonging to the same population of the sample used here (sector, region, and size, for instance), could be profiled using these three 'fundamental' characteristics.

How can we calculate the value of the three components, starting from the original variables? Table 4-13 shows the coefficients that link the original variables to the new ones.

**TABLE 4-13** The Link between Variables and Components.

| Original Variables | COMP1 | COMP2 | COMP3 |
|---|---|---|---|
| ROE | 0.133 | 0.479 | 0.048 |
| ROI | 0.176 | 0.437 | −0.091 |
| CR | 0.316 | −0.216 | 0.052 |
| QR | 0.320 | −0.172 | −0.040 |
| MTCI | −0.323 | 0.082 | 0.178 |
| SHARE (%) | −0.020 | 0.142 | −0.668 |
| R&S (%) | −0.078 | −0.156 | −0.646 |



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The table can be seen as a common output of linear regression analysis. Given a new $i$th observation, the $j$th component's value $S_{comp\ j}$ is calculated by summing up the original variables $x_i$ multiplied by the coefficients, as shown below:

$$S_{comp1} = Roe_i \times 0{,}133 - Roi_i \times 0{,}176 + CR_i \times 0{,}316 + QR_i \times 0{,}320 - MTCI_i \times (0{,}323) - SHARE_i \times (0{,}020) - R\&S_i \times (0{,}078)$$

This value is expressed in the same scale of the original variables, that is, it is not standardized. All the components are in the same scale, so they are comparable with one another in terms of mean (higher, lower) and variance (high/low relative variability). Very often, this is a desirable feature for the model builder. Principal components maintain the fundamental information on the level and variance of the original data. Therefore, principal components are suitable to be used as independent variables to estimate models, as all other variables used in LDA, logistic regression and/or cluster analysis. In this perspective, principal component analysis could be employed in model building as a way to pre-filter original variables, reducing their number, avoiding the noise of idiosyncratic information.

Now, consider 'factor analysis', which is similar to principal component; it is applied to describe observed variables in terms of fewer (unobserved) variables, known as 'factors'. The observed variables are modeled as linear combinations of the factors.

Why do we need factors? Unless the latent variable of the original $q$ variables dataset is singular, the principal component analysis may not be efficient. In this case, factor analysis may be useful.

Assume that there are three 'true' latent variables. The principal component analysis attempts to extract the most common first component. This attempt may not be completed in an efficient way, because we know that there are three latent variables and each one will be biased by the effect of the other two. In the end, we will have an overvaluation of the first component contribution; in addition, its meaning will not be clear, because of the partial overlapping with the other two latent components. We can say that, when the likely number of latent variables is more than one, we will have problems in effectively finding the principal component profiles associated to the 'true' underlying fundamentals. So, the main problem of principal components analysis is to understand what the meaning of the new variables is, and to use them as more efficient combination of the original variables.

This problem can be overcome using the so called 'factor analysis', that is, in effect, often employed as the second stage of principal component analysis. The role of this statistical method is to:

- define the minimum statistical dimensions needed to efficiently summarize and describe the original dataset, free of information redundancies, duplications, overlapping, and inefficiencies;
- make a transformation of the original dataset, to give the better statistical meaning to the new latent variables, adopting an appropriate optimization algorithm to maximize the correlation with some variables and minimize the correlation with others.

In this way, we are able to extract the best information from our original measures, understand them and reach a clear picture of what is hidden in our dataset and what is behind the borrowers' profiles that we directly observe in raw data.

Thurstone (1947), an American pioneer in the fields of psychometrics and psychophysics, described the set of criteria needed to define 'good' factor identification for the first time. In a correlation matrix showing coefficients between factors (in columns) and original variables (in rows), the required criteria are:

1. each row ought to have at least one zero;
2. each column ought to have at least one zero;
3. considering the columns pair by pair, as many coefficients as possible have to be near zero in one variable and near one in the other; there should be a low number of variables with value near one;
4. if factors are more than two, in many pairs of columns some variables have to be near zero in both columns.

In reality, these sought-after profiles are difficult to reach. To better target a factors' structure with these features, a further elaboration is needed; we can apply a method called 'factor rotation', a denomination derived from its geometrical interpretation. Actually, the operation could be thought of as a movement of the variable in the $q$-dimensions hyperspace to better fit some variables and to get rid of others, subject to the condition to have orthogonal factors one to the other. This process is a sort of factors adaptation in the space, aimed at better arrang-



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ing the fit with the original variables and achieving more recognizable final factors.

To do this, factors have to be isomorphic, that is, standardized numbers, in order to be comparable and easily transformable. So, the first step is to standardize the principal components. Then, factor loadings (i.e., the value of the new variables) should be expressed as standardized figures (mean equal to zero and standard deviation equal to one). Factor loadings are comparable to one another but are not comparable (for range and size) with the original variables (on the contrary it is possible for principal components).

Furthermore, the factors depend on the criteria adopted to conduct the so-called 'rotation'. There are many criteria available. Among the different solutions available, there is the so-called 'varimax method.'[2] This rotation method targets either large or small loadings of any particular variable for each factor. The method is based on an orthogonal movement of the factor axes, in order to maximize the variance of the squared loadings of a factor (column) on all of the variables (rows) in a factor matrix. The obtained effect is to differentiate the original variables by extracted factors. A varimax solution yields results which make it as easy as possible to identify each variable with a single factor. In practice, the result is reached by iteratively rotating factors in pairs; at the end of the iterative process, when the last round does not add any new benefit, the final solution is achieved. The Credit Risk Tracker model, developed by the Standards & Poor's rating agency for unlisted European and Western SME companies, uses this application.[3]

Another example is an internal survey, conducted at Istituto Bancario Sanpaolo Group on 50,830 financial reports, extracted from a sample of more than 10,000 firms, collected between 1989 and 1992. Twenty-one ratios were calculated; they were the same used at that time by the bank to fill in credit approval forms; two dummy variables were added to take the type of business incorporation and the financial year into consideration. The survey objective was a preliminary data cleansing trying to identify clear, dominant profiles in the dataset, and separating 'outlier' units from the largely homogeneous population. The elaboration was based on a two-stage approach, the first consisting of factor analysis application, and the second using factors profiles to work out clusters of homogenous units.

Starting from 21 variables, 18 were the components with an eigenvalue of more than one, accounting for 99% of total variance; the first five, on which we will concentrate our analysis, accounted for 94%. Then, these 18 components were standardized and rotated. The explanation power was split more homogeneously through the various factors. The first five were confirmed as the most common and were able to summarize 42% of total variance in a well and identifiable way; the 'Cattell scree test' (that plots the factors on the X axis and the corresponding eigenvalues on the Y-axis in descending order) revealed a well established elbow after the first five factors and the others. The' remaining 13 factors were rather a better specification of individual original attributes than factors which were able to summarize common latent variables. These applications were very useful, helping to apply at best cluster analysis that followed, conducted on borrowers' profiles based on common features and behaviors. Table 4-14 reports original variables, means, and factors structures, that is, the correlation coefficients between original variables and factors.

Coming to the economic meanings of the results of the analysis, it can be noted that the first six variables derive from classical ratios decomposition. Financial profitability, leverage, and turnover are correlated to three different, orthogonal factors. As a result, they are three different and statistically independent features in describing a firm's financial structure. This is an expected result from the firm's financial theory; for instance, from Modigliani–Miller assertions that separated operations from financial management. Moreover, from this factor analysis, assets turnover is split into two independent effects, that of fixed assets turnover on one side and that of working capital turnover on the other. This interpretation is very interesting. Very similar conclusions emerge from the PIMS econometric analysis, where capital intensity is proven to highly influence strategic choices and competitive positioning among incumbents and potential competitors, crucially impacting on medium term profits and financial

[2] Varimax rotation was introduced by Kaiser (1958). The alternative called 'normal-varimax' can also be considered. The difference is the use of a rotation weighted on the factor eigenvalues (Loehlin, 2003; Basilevsky, 1994). For a wider discussion on the Kaiser Criterion see Golder and Yeomans (1982).

[3] Cangemi, De Servigny, and Friedman, 2003; De Servigny *et al.,* 2004.



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**TABLE 4-14** Correlation among Factors and Variables in a Sample of 50,830 Financial Reports (1989–1992)

| | | Fact1 | Fact2 | Fact3 | Fact4 | Fact5 |
|---|---|---|---|---|---|---|
| **Ratios** | **Means** | **Correlation coefficients (%)** | | | | |
| RoE | 6.25% | 43.9 | | | –11.4 | |
| RoI | 7.59% | 87.3 | | –20.3 | | |
| Total leverage | 5.91x | | 96.8 | | 16.7 | |
| Shareholders' profit on industrial margin | –0.28% | 37.2 | | | | |
| RoS | 5.83% | 94.6 | | | | |
| Total assets turnover | 1.33x | | | –55.3 | | 33.5 |
| Gross fixed assets turnover | 4.37x | | 21.3 | | | 89.9 |
| Working capital turnover | 1.89x | | | –64.3 | | |
| Inventories turnover | 14.96x | | | –12.5 | | |
| Receivables (in days) | 111.47 | | | 96.8 | | |
| Payables (in days) | 186.34 | | 11.8 | 28.5 | | |
| Financial leverage | 4.96x | | 97.0 | | 16.2 | |
| Fixed assets coverage | 1.60x | | –16.9 | | –20.5 | 22.8 |
| Depreciation level | 54.26% | | | | –18.5 | |
| Sh/t financial gross debt turnover | 1.39x | | –28.1 | 10.6 | –48.7 | |
| Sh/t net debt turnover | 0.97x | | –24.9 | 18.2 | –44.7 | |
| Sh/t debt on gross working capital | 25.36% | | 12.2 | | 97.0 | |
| Sales (ITL.000.000) per employee | 278.21 | | | –14.8 | 22.2 | |
| Added value per employee (ITL.000.000) | 72.96 | 27.3 | | | | |
| Wages and salaries per employee (ITL.000.000) | 41.92 | | | | | |
| Gross fixed assets per employee (ITL.000.000) | 115.05 | | –10.6 | | | –18.9 |
| Interest payments coverage | 2.92x | 49.6 | –15.2 | | –26.2 | |
| 0 = partnership. 1 = stock company | 0.35 | | 11.7 | | | 10.2 |
| Year end (1989, 1990, 1991, 1992) | 1990.50 | | | | | |
| | % of variance explained by each factor | 10.6 | 10.0 | 8.7 | 7.4 | 5.1 |
| | % cumulated variance explained | 10.6 | 20.7 | 29.4 | 36.8 | 41.9 |

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returns. The last factor regards the composition of firm's financial sources, partially influenced by the firm's competitive power in the customer/supply chain, with repercussions on leverage and liabilities arrangement.

Eventually, a final issue regards the economic cycle. The financial years from 1989 to 1992 were dramatically different. In particular, 1989 was one of the best years since the Second World War; 1992 was one of the worst for Italy, culminating with a dramatic devaluation of the currency, extraordinary policy measures and, consequently, the highest default rate in the industrial sectors recorded till now. We can note that the effect of the financial year is negligible, stating that the economic cycle is not as relevant as it is often assumed in determining the structural firms' profiles.

The cluster analysis that followed extracted 75% of borrowers with high statistical homogeneity and, based on them, a powerful discriminant function was estimated. The remaining 25% of borrowers showed high idiosyncratic behaviors, because they were start-ups, companies in liquidation, demergers or recent mergers; or simply data loading mistakes, or cases with too many missing values. By segregating these units, a high improvement in model building was achieved, avoiding statistical 'white noise' that could give unreliability to estimates.

The final part of this section is devoted to the so-called 'canonical correlation' method, introduced by Hotelling in the 1940s. This is a statistical technique used to work out the correspondence between a set of dependent variables and another set of independent variables. Actually, if we have two sets of variables, one dependent ($Y_i$) and another to explain the previous one (independent variables, $X_i$), then canonical correlation analysis enables us to find linear combinations of the $Y_i$ and the $X_i$ which have a maximum correlation with each other. Canonical correlation analysis is a sort of factor analysis in which the factors are extracted out of the $X_i$ set, subject to the maximum correlation with the factors extracted out of the $Y_i$ set. In this way we are able to work out:

- how many factors (i.e., fundamental or 'basic' information) are embedded in the $Y_i$ set,
- the corresponding factors out of the $X_i$ set that are maximally correlated with factors extracted from the $Y_i$ set.

*Y* and *X* factors are orthogonal to one another, guaranteeing that we analyze actual (or latent) dimensions of phenomena underlying the original dataset.

In theory, canonical correlation can be a very powerful method. The only problem lies in the fact that, at the end of the analysis, we cannot rigorously calculate factors' scores, and, also, we cannot measure the borrowers' profile in new dependent and independent factors, but instead we can only generate proxies.

A canonical correlation is typically used to explore what is common amongst two sets of variables. For example, it may be interesting to explore what is explaining the default rate and the change of the default rate on different time horizons. By considering how the default rate factors are related to the financial ratios factors, we can gain an insight into what dimensions were common between the tests and how much variance was shared. This approach is very useful before starting to build a model based on two sets of variables; for example, a set of performance measures and a set of explanatory variables, or a set of outputs and a set of inputs. Constraints could also be imposed to ensure that this approach reflects the theoretical requirements.

Recently, on a database of internal ratings, in SanPaoloIMI a canonical correlation analysis has been developed. It aims at explaining actual ratings and changes (*Y* set) by financial ratios and qualitative attributes (*X* set). The results were interesting: 80% of the default probability (both in terms of level and changes) was explained by the first factor, based on high coefficients on default probabilities; 20% was explained by the second factor, focused only on changes in default probability. This second factor was highly correlated with a factor extracted from the *X* set, centered on industrial and financial profitability. The interpretation looks unambiguous: part of the future default probability change depends on the initial situation; the main force to modify this change lies in changes in profitability. A decline in operational profits is also seen as the main driver for the fall in credit quality and vice versa.

Methods like cluster analysis, principal component, factor analysis, and canonical correlation are undoubtedly very attractive because their potential contribution in the cleansing dataset and refining the data interpretation and the model building approach. Considering clusters, factors or canonical correlation structures help to better master



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the information available and identify the borrower' profile determinants. Starting from the early 1980s, these methods achieved a growing role in statistics, leading to the so-called 'exploratory multidimensional statistical analyses'; this was a branch of statistics born in the 1950s as *'explorative statistics'* (Tukey, 1977). He introduced the distinction between *exploratory data analysis* and *confirmatory data analysis,* and stated that the statistical analysis often gives too much importance to the latter, undervaluing the former. Subsequently, this discipline assumed a very relevant function in many fields, such as finance, health care, marketing, and complex systems' analysis (i.e., discovering the properties of complex structures, composed by interconnected parts that, as a whole, exhibit behaviors not obvious from the properties of the individual parts).

These methods are different in role and scope from discriminant or regression analyses. These last two methods are directly linked with decision theory (which aims at identifying values, uncertainties and other issues relevant for rational decision making). As a result of their properties, discriminant and regression analyses permit inferring properties of the 'universe' starting from samples. Techniques of variance reduction and association do not share these properties; they are not methods of optimal statistical decision. Their role is to arrange, order, and compact the available information, to reach better interpretations of information, as well as to avoid biases and inefficiencies in model building and testing. When principal components are used as a pre-processor to a model, their validity, stability and structure has to be tested over time in order to assess if solutions are still valid or not. In our experience, the life cycle of a principal component solution is around 18–24 months; following the end of this period, important adjustments would be needed.

Conversely, these methods are very suitable for numerical applications, and neural networks in particular, as we will subsequently examine.

## Cash Flow Simulations

The firm's future cash flow simulation ideally stays in the middle between reduced form models and structural models. It is based on forecasting a firm's pro-forma financial reports and studying future performances' volatility; by having a default definition, for instance, we can see how many times, out of a set of iterative simulations, the default barrier will be crossed. The number of future scenarios in which default occurs, compared to the number of total scenarios simulated, can be assumed as a measure of default probability.

Models are based partly on statistics and partly on numeric simulations; the default definition could be exogenously or endogenously given, due to a model's aims and design. So, as previously mentioned, structural approaches (characterized by a well defined path to default, endogenously generated by the model) and reduced form approaches (characterized by exogenous assumptions on crucial variables, as market volatility, management behaviors, cost, and financial control and so forth) are mixed together in different model architectures and solutions.

It is very easy to understand the purposes of the method and its potential as a universal application. Nevertheless, there are a considerable number of critical points. The first is model risk. Each model is a simplification of reality; therefore, the cash flow generator module cannot be the best accurate description of possible future scenarios. But, the cash flow generator is crucial to count expected defaults. Imperfections or inaccuracies in its specification are vital in determining default probability. Hence, it is evident that we are merely transferring one problem (the direct determination of default probability through a statistical model) to another (the cash flow generator that produces the number of potential default circumstances). Moreover, future events have to be weighed by their occurrence in order to rigorously calculate default probabilities. In addition, there is the problem of defining what default is for the model. We do not know if and when a default is actually filed in real circumstances. Hence, we have to assume hypotheses about the default threshold. This threshold has to be:

- not too early, otherwise we will have many potential defaults, concluding that the transaction is very risky (but associated LGD will be low),
- not too late, otherwise we will have low default probability (showing a low risk transaction) but we could miss some pre-default or soft-default circumstances (LGD will be predicted as severe).

Finally, the analysis costs have to be taken into consideration. A cash flow simulation model is very often company specific or, at least, industry specific; it has to be calibrated with particular circumstances and supervised by the firm's management and a competent analyst. The



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