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End of Studies Project

Topic :

The Value at Risk approach to evaluating credit risk within the Bank of Local Development (BDL)

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Dedication

This work is wholeheartedly dedicated to my family, my mom, my sisters, all my friends. Thank you for supporting me every step of the way.

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Abbreviations

VaR: Value at Risk

CSFB: Credit Suisse First Boston

KSF: Key Success Factor

BDL: Banque de Développement Local

SME: Small and Medium sized Entreprises

BCBS: Basel Committee on Banking Supervision

PD: Probability of Default

LGD: Loss Given Default

EAD: Exposure at Default

EL: Expected Loss

UL:Unexpected Loss

EU: European Union

OECD: Organisation for Economic Co-operation and Development

RWA: Risk Weighted Assets

IRB: Internal Ratings-Based

AMA:Advanced Measurement Approach

LCR: Liquidity Coverage Ratio

NSFR: Net Stable Funding Ratio

S&P: Standards & Poors

RR: Recovery Rate

EDF: Expected Default Frequency

FX: Foreign Exchange

BT: British Telecom

LIBOR:London Interbank Offered Rate

CDO: Collateralised Debt Obligation

RAROC: Risk-Adjusted Return On Capital

PC: Personal Computer

CDS: Credit Default Swap

CSFP: Credit Suisse Financial Products

ABS: Asset-Backed Security

MBS: Mortgage-Backed Security

PGF: Porbability Generating Function

CPA: Crédit Populaire d'Algérie

BNA: Banque Nationale d'Algérie

BEA: Banque extérieure d'Algérie

IT:Information Technology

ANSEJ:L'Agence Nationale de Soutien à l'Emploi des Jeunes

CNAC: Caisse nationale d'assurance-chômage

ANGEM: Agence Nationale de gestion du Micro-crédit

DASC:Direction d'Analyse et de Suivi des Crédits

DGE: Direction des Grandes Entreprises

DRF: Direction des Risques Financiers

PDF: Probability Density Function

RC: Risk Contribution

Introduction

The financial environment has undergone several shocks over the past decades which have strongly threatened its existence and functioning. The banking system system has shown itself to be very permeable to this drift, as shown by the failure of several banks (Continental Illinois in 1984, the Texas banks from 1985 onwards and Lehman Brothers in 2008) and the reappearance of a financial crises on average every ten years (the stock market crash in 1987, the Asian crisis in 1997 and the subprime crisis in 2007). This has demonstrated the harmful role that a fragile banking system can play in amplifying financial disorder.

The consequences are multiple, although everyone admits that the main cause is the intense competition pushing banks to launch themselves in a frantic race for market shares, very often to the detriment of the control and management of financial risks.

Despite the magnitude of the financial risks and the tragic effects of the financial crises that threaten the stability of the banking environment, it was not until the early 1990s that risk management became effective. At that time, banks tended to strengthen their capital base in accordance with the requirements of the Basel agreement of 1988.

A few years later, the Basel Committee, aware of the limitations of its first Basel I agreement, expressed its will to rework it and introduced a new Basel II, the founding principle of which is to reward the best practices in risk measurement and management and to allow banks with a long track record in this area to use their own know-how and techniques to assess their risk, particularly credit risk.

In the image of Basel I and Basel II, credit risk has become the preoccupation of financial engineers, they have launched into the development of new techniques allowing them to better manage this risk which has become the major concern of banks because of its disastrous danger.

Since then the advances in the area of credit risk have been numerous, sophisticated, and even overly complex at times. The literature on the subject is very abundant and there are currently several models for understanding this counterparty risk. The development by banks of internal models based on a Value at Risk (VaR) approach, in particular, has considerably increased their ability to manage the risks of their credit activities. This concept of Value at Risk is derived from market risk management and is at the heart of several current credit risk management models; CreditMetrics from JP Morgan, Portfoloio Manager from Moody's or CreditRisk+ from Credit Suiss First Boston. Therefore, banks adopting such models find themselves with a real key with a real key success factor (KSF) compared to the competition. This is another challenge in managing credit risk.

Today, it is possible to statistically quantify the probability of default, the expected loss and the maximum loss that a bank can incur on a portfolio of loans, the latter is commonly called the Value at Risk.

These measures are some of the most important data to have beforehand because of the sensitivity of the information it contains. Thus, our goal in this thesis is to develop a model that is to develop a model that will allow us to measure the VaR.

However, Algerian banks have not yet adjusted to all these tools, since they evolve in a context of economic difficulty contrasted by an important decrease of the treasury, only shareholder of the public banks like the Bank of Local Development (BDL) , it really finances alone nearly 90% of the economy, resources are becoming expensive, and adequate risk management is becoming more and more important, even essential. In addition, it should be noted that, under the instruction of the gouvernment , in order to escape from the dependence on oil and gas exports, the tendency of public banks in terms of financing of SMEs which represent the main vector of wealth and employement, this gives another justification to the implementation of an effective model of credit risk management favoring a more intelligent management of risks that the bank accepts on these financings.

It is in the context outlined above that we will attempt to answer our main question, which is the following:

“How can the Value at Risk approach be used by a banking institution in order to evaluate its credit risk?”

In order to properly comprehend this central issue, the answer to the secondary questions is necessary:

- What are the risks faced by banks? and what are the means available to the bank to manage them according to national and international prudential regulations?

- What are is the Value at Risk approach? And what are its models?

- How can such a tool be applied in practice to best measure the credit risk in an Algerian bank, in particular the BDL?

In order to provide answers to the questions raised above, we have structured our work as follows:

- We will begin with a first chapter devoted to the presentation of the generalities on credit risk, , the challenges of modeling, as well as regulatory developments in the area of credit risk.

- The second chapter will delve into the Value at Risk approach to risk management, highlighting its different models, and how those operate from a technical standpoint.

-The last part of this work, concerns a case study that we carried out during our practical training at the during our internship within the Bank of Local Development. We will expose how a tool such as CreditRisk+ can be implemented and how it can be used to better evaluate credit risk by interpreting the different results.

Chapter 1 : Fondemental notions in credit risk management

Chapter introduction

Banks are an indispensable intermediary for the functioning of an economy. It is at the crossroads of almost all economic relations. Through this intermediation role, banks collect funds from the public and distributes them to those who need them in the form of credit. This activity exposes them to certain risks, in particular credit risk.

Credit risk is one of the oldest risks faced by banks, and it is the main source of financial losses. Thus, this risk, in the different ways that it reveals itself , is at the heart of the banking concerns. For a better management of this hazard, a relevant regulation has been set up.

In this context, the interest of this first chapter consists in :

First of all, to expose the general aspects relating to credit risk.

Then, in a second section, to review the banking regulation in terms of credit risk.

Finally, we will present some concepts related to credit risk and its evaluation, which are necessary for the construction of a model.

Section 1: Basic concepts about credit risk

1.1.Definition of risk

Risk in banking refers to the potential loss that may occur to a bank due to the happening of some events. Risk arises because of the uncertainty associated with events that have the potential to cause loss; an event may or may not occur, but if it occurs it causes loss. Risk is primarily embedded in financial transactions, though it can occur due to other operational events. It is measured in terms of the likely change in the value of an asset or the price of a security/commodity with regard to its current value or price. When we deal with risks in banking, we are primarily concerned with the possibilities of loss or decline in asset values from events like economic slowdowns, unfavorable fiscal and trade policy changes, adverse movement in interest rates or exchange rates, or falling equity prices. Banking risk has two dimensions: the uncertainty—whether an adverse event will happen or not—and the intensity of the impact—what will be the likely loss if the event happens (that is, if the risk materializes). Risk is essentially a group characteristic; it is not to be perceived as an individual or an isolated event. When a series of transactions are executed, a few of them may cause loss to the bank, though all of them carry the risk element.[1]

1.2.Categories of risk

Banks face two broad categories of risks: business risks and control risks. **Business risks** are inherent in the business and arise due to the occurrence of some expected or unexpected events in the economy or the financial markets, which cause erosion in asset values and, consequently, reduction in the intrinsic value of the bank. The money lent to a customer may not be repaid due to the failure of the business, or the market value of bonds or equities may decline due to the rising interest rate, or a forward contract to purchase foreign currency at a contracted rate may not be settled by the counterparty on the due date as the exchange rate has become unfavorable. These types of business risks are inherent in the business of banks. Credit risk, market risk, and operational risk, the three major business risks, have several dimensions, and therefore require an elaborate treatment.

[1] (Wiley Finance) Amalendu Ghosh - Managing Risks in Commercial and Retail Banking-Wiley (2012)

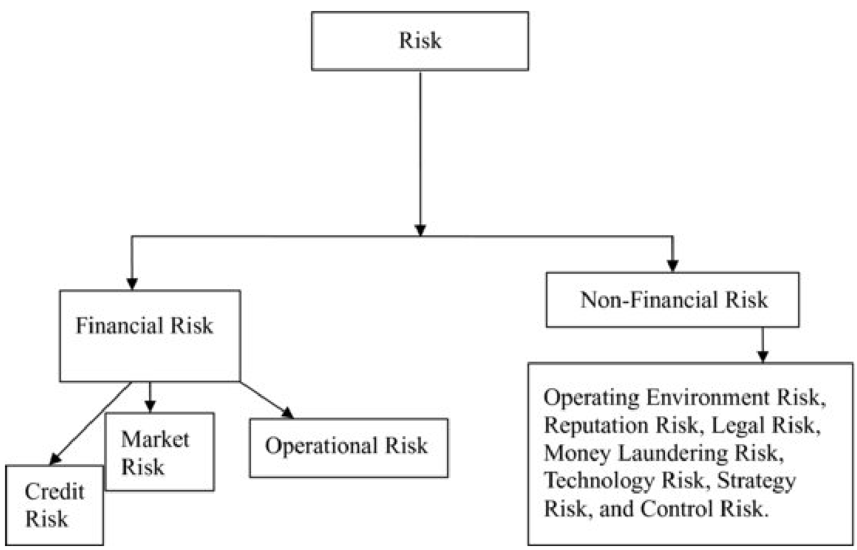
Control risk refers to the inadequacy or failure of control that is intended to check the intensity or volume of business risk or prevent the proliferation of operational risk. Inadequacy in control arises due to the lack of understanding of the entire business process, while failure in control arises due to complacency or laxity on the part of the control staff. Let us suppose that the bank has estimated an average loan loss of 5 percent in its credit portfolio as per its internal model. The actual loan loss will be more than 5 percent, if adequate control is not exercised on credit sanction and credit supervision. If the loan sanction standard is compromised or collateral is not obtained in accordance with the prescribed norms, or laxity in control prevails over the supervision of borrowers' business and accounts, the level of credit risk will be higher than that estimated under an internal model. Business risk will be higher if the control system fails to detect the irregularities in time. Banks must have an elaborate control system that spreads over credit, investment, and other operational areas.

The risks can also be classified into two other categories: **financial risk** and **nonfinancial risk**. Financial risks inflict loss on a bank directly, while nonfinancial risks affect the financial condition in an indirect manner. Credit, market, and operational risks are financial risks since they have a direct impact on the financial position of a bank. For example, if the market value of a bond purchased by the bank falls below the acquisition price, the bank will incur a loss if it sells the bond in the market. Reputation risk, legal risk, money laundering risk, technology risk, and control risk are nonfinancial risks because they adversely affect the bank in an indirect manner. Business opportunities lost, and consequently income lost, on account of negative publicity against a bank that impairs its reputation, or compensation paid to a customer in response to an unfavorable decree from a court of law against the bank, are examples of nonfinancial risk.

The impact of financial risks can be measured in numerical terms, while that of nonfinancial risks is most often not quantifiable. The impact of nonfinancial risks can be assessed through scenario analysis and indicated in terms of severity such as low, moderate, and high. Business risks comprise both financial and nonfinancial categories of risks, whereas control risk is only a nonfinancial risk as it impacts a bank in an indirect way. Consequently, risk management in banking is concerned with the assessment and control of both financial and nonfinancial risks. Bank regulators and supervisors caution banks about the dangers of ignoring risks and want them to understand the implications of financial and nonfinancial risks and develop methods to assess and manage those risks.

A typical risk can occur from multiple sources. For example, credit risk occurs from loans and advances, investments, off-balance-sheet items including derivative products, and cross-border exposures. Likewise, market risk occurs from changes in the interest rate that affects banking book and trading book exposures, changes in bond/equity/commodity prices, and change in the foreign exchange rate. The boundaries between different types of risks are sometimes blurred. A loss due to shrinking credit spreads may be either credit risk loss or market risk loss. Credit risk and market risk may sometimes overlap. Capital risk and earning risk are not risks by themselves for a bank. They are the two financial parameters that absorb the ultimate loss from the materialization of risks. The minimization (or optimization) of the impact of business risk and control risk on the capital and earnings of banks is the ultimate goal of risk management.

Figure 1: Types of risk



1.3.Credit risk:

The Basel Committee on Banking Supervision (BCBS) has defined credit risk as the potential that a bank borrower or counterparty will fail to meet its obligations in accordance with the

agreed terms[2]. Credit risk, also called default risk, arises from the uncertainty involved in repayment of the bank's dues by the counterparty on time. Credit risk has two dimensions: the possibility of default by the counterparty on the bank's credit exposure and the amount of loss that the bank may suffer when the default occurs. The default usually occurs because of inadequacy of income or failure of business. But often it may be willful, because the counterparty is unwilling to meet its obligations though it has adequate income. .
Even without the extreme case of a borrower becoming insolvent, credit risk can be defned as the eventuality that an unexpected variation in a borrower’s creditworthiness may cause an unexpected variation in the value of the credit. It can be classifed as follows:

A. Credit default risk is the risk of an identifable loss by a bank that believes it probable that a creditor will not fully honour their credit obligations or that they may encounter signifcant delays in the payment of a substantial obligation.

B. Concentration risk is the risk associated with a single or a group of exposures that may cause signifcant losses that can undermine a bank’s own sustainability. This concentration may be towards a single obligation or an entire sector.

C. Country risk is the risk of a loss arising from a state freezing its payments in foreign currency (transfer/conversion risk) or defaulting its payments (sovereign default risk).

1.3.1. Credit risk factors

Credit risk is typically represented by means of three factors: default risk, loss risk and exposure risk:

1.3.1.1. **Default risk (PD)**: The default risk is the probability that a default event occurs. This probability is called the probability of default (PD). The probability has values between 0 and 1. There are many definitions of a default event. The most common definition of a default event is a payment delay of at least 3 months. Other definitions may add specific events. The default risk depends on many factors. Counterparts with a weak financial situation, high debt burden, low and unstable income have a higher default probability. Apart from quantitative factors, qualitative factors like sector information and management quality also allow discriminating between counterparts with high and low

[2] Principles for the Management of Credit Risk, BCBS, September 2000.

default risk. In markets with increased competition, reducing industry margins, and a macroeconomic downturn, the default rates are expected to be higher than on average. Some counterparts have lower risk than that measured on a stand-alone basis: they can receive support from relatives, the mother company or even the state when it is a critical company for the society.

The default risk is assessed internally by means of scoring systems and human expert judgment. The continuous default probability is typically represented on an internal rating scale with an ordinal ranking of the risk and discrete, increasing default probabilities. There also exist external rating agencies that provide an independent and external assessment of the default risk for investors in debt and other products.

In most cases, default risk is defined on a counterpart, not on a product. When a counterpart defaults on one loan or obligation, it is likely to default also on its other loans by the contamination principle. In particular asset classes, the contamination principle may not always hold and default risk can also be product specific.

In the case of a default, the actual loss depends on the loss given default (LGD) and the exposure at default (EAD). These values are discussed below.

1.3.1.2.**Loss risk (LGD)**: The loss risk determines the loss as a fraction of the exposure in the case of default. In the Basel II terminology, this parameter is known as the loss given default (LGD). In the case of no loss, the LGD is equal to zero. When one loses the full exposure amount, the LGD is equal to 100%. A negative LGD indicates a profit (e.g., due to penalty fees and interest rate). In some cases, the LGD can be above 100%, e.g., due to litigation costs and almost zero recovery from the defaulted counterpart. In some textbooks, one also uses the related concept of the recovery rate: the fraction of the total amount that one recovers. Both the loss given default and the recovery rate sum up to one.

The loss given default or recovery rate are not fixed parameters. These values fluctuate from one defaulted product to another. Some counterparts may cure from default and repay all the debt and delayed payments. For others, an agreement between the defaulted debtor and all the creditors may result in a distressed exchange agreement where all

involved parties carry part of the loss. In the worst case, the default results in a bankruptcy procedure with high losses and the end of the bank–customer relation.
The type of default may have a big impact on the actual loss, but may not be known at the moment of default and certainly not at the moment of the investment. In the case of a default, banks have the right to take legal actions. The timing and type of actions may also impact the actual recovery.
In practice, the LGD values are observed to vary quite a lot and depend upon the type of default and its resolution:

A. Cure: The financial health of the defaulted counterpart is cured shortly after the default event, e.g., because of an additional income or a shareholder intervention. The counterpart continues to fulfil its contractual obligations. There is no significant loss for the bank and the relation with the customer is not impacted.
B. Restructuring: The defaulted counterpart is able to recover from default after a debt restructuring, e.g., debt renegotiations resulting in a longer maturity and partial debt forgiveness. The bank–customer relation is damaged, but is often maintained. The bank accepts a medium loss to avoid higher losses in a liquidation or bankruptcy procedure.
C. Liquidation: The customer's facilities are liquidated, collateral is seized. The relationship with the customer is ended. Liquidation procedures may involve high legal costs and losses are typically high.

It is difficult to predict the resolution type before default. On average, liquidation is expected to occur more for the weakest counterparts for which investors and banks are less eager to reinvest.

In the cases of high default and loss risk, the bank will try to reduce the loss risk by requiring collateral or guarantees. In the case of a default event, the bank will try to recover the outstanding debt and delayed payments from the collateral, guarantees and the counterpart. Of course, the LGD will depend on the value of the collateral at the time of sale and whether it is legally and practically possible to seize the collateral and sell it.

When guarantees are taken, a better protection is obtained with a financially sound guarantor that is not dependent on the obligor's risk.

Other factors that determine the loss given default have been studied, but depend on the particular case. These include characteristics of the borrower (default risk, amount of debt, income, . . .), characteristics of the product (seniority, collateral, amount), overall characteristics of the economy and the sector and features of the bank–customer relationship.

The LGD is measured on a product basis. It has typically values between 0 and 100% and is either represented in a continuous way or by means of loss grades. Some banks have a separate LGD rating scale on top of the PD rating scale, other banks combine the LGD and PD information on an expected loss (EL = PD × LGD) rating scale. Recently, external rating agencies have also begun to quantify explicitly the loss risk in terms of recovery ratings; complementary to the PD ratings.

1.3.1.3. **Exposure risk (EAD)**: The exposure at the time of default (EAD) may not be known beforehand. For some products like a bond or a straight loan, the amount is a fixed amount. For credit cards or overdraft facilities, the amount varies with the liquidity needs of the borrower. The counterpart can take cash up to a negotiated credit limit. The credit limit bounds the commitment of the bank. Other products have no explicit limit, but each additional drawing needs approval of the bank. The uncertainty on the exact amount at risk at the very moment of a future default is exposure risk. Privately negotiated derivative product contracts also bear exposure risk: if the counterpart of the derivative products defaults during the contract, one is exposed to the net positive value of the replacement cost of the contract. This specific type of risk is called counterpart credit risk.

A typical observation is that financially stressed counterparts have high liquidity needs and tend to use most of the limits. The bank will try to protect itself against such additional drawings by additional clauses in the contract that allow reduced limits or contract renegotiation when specific events occur (e.g., rating downgrade, key ratios drop

below threshold limits). These clauses are called covenants or material adverse clauses. Some banks actively manage limits of their most risky counterparts.
Apart from product and covenant properties, one can expect that the exposure risk depends on features of the borrower and on the general state of the economy.
The exposure risk is typically expressed in the currency of the product or of the bank (euro, dollar, yen, . . .).

These risk factors also depend on the maturity of the contract. The longer the contract, the higher the uncertainty and the risk. In most applications one measures or expresses the credit risk on a 1-year horizon. The estimation, modelling and management of the default risk is the most developed. Both LGD and EAD risk received a lot of attention with the new Basel Capital Accord.

For a coherent measurement and management of credit risk, it is necessary to have consistent definitions. The LGD and EAD depend upon the default definition and the LGD is the proportional loss with respect to the EAD. These definitions need to be consistent and coherent to express the risk correctly and to allow comparison and benchmarking of risk levels across different products, business lines, and financial institutions. The Basel II Capital Accord has provided a first step towards a uniform default definition and provides guidelines for LGD and EAD as well: the bank's capital requirements will depend on internally estimated risk levels defined by the Basel II rules.

Section 2: Evolution of credit risk regulation

The determination of a bank's optimal capital level is an issue on which academics, bankers and regulators have different views. The solution that regulators provide consists of the regulatory capital requirements proposed by the Basel Committee on banking supervision (BCBS) in 1988, and that the supervisory authorities of over 150 countries have implemented. The Basel Capital Accord, originally intended specifically for large, internationally active banks, has in practice served as the basis for the risk-based capital adequacy standards for most banking organizations worldwide. In fact, although the Basel Accord applies to the international banks in member countries, many countries require all their banks to adhere to the Basel rules. For example, in the EU the Basel Accord has been introduced via directives and is mandatory for all European financial institutions.

Over the 32 years since the Basel Accord was adopted, the framework has been repeatedly refined to take into account changes in banking and the banking system. In particular, capital requirements originally set in 1996 to cover credit risk only were extended to market risks and in 2004 to operational risks. Furthermore, in 2004 the Basel Committee completely revised the 1988 approach to credit risk.

2.1. The 1988 Capital Accord

The 1988 Accord, now familiarly known as Basel I, assessed capital mainly in relation to credit risk, and addressed other risks only implicitly, effectively loading all regulatory capital requirements onto measures of credit risk.

Basel I required banks to have regulatory capital amounting to at least 8 percent of their total risk-weighted assets:

$$\text{Capital Ratio}_{\text{Basel 1}}{}^{3} = \frac{\text{Regulatory Capital}}{\text{Risk-Weighted Assets}} \geq 8\%$$

2.1.1. Regulatory capital

According to Basel I, the key elements of capital are equity capital and disclosed reserves. These key elements are the only components common to all countries' banking systems, they are wholly visible in the published accounts, and they are the basis on which most market judgments of capital adequacy are made. Notwithstanding this emphasis, member countries of the BCBS have suggested that there are a number of other elements of a bank's capital base that should be included within the system of measurement.

The BCBS concluded that for supervisory purposes capital should be defined in two tiers in a way that will require at least 50 percent of a bank's capital base to consist of a core element

[3] The capital ratio is calculated using the definition of regulatory capital and risk-weighted assets (BCBS, 1988).

mainly comprised of equity capital[4] and disclosed reserves[5] (Tier 1). In the case of consolidated accounts, Tier 1 will also include minority interests in the equity of subsidiaries that are not wholly owned. This basic definition of capital excludes revaluation reserves and cumulative preference shares.

In 1998, the BCBS, noting that certain banks had issued a range of innovative capital instruments with the aim of generating Tier 1 regulatory capital, decided to limit acceptance of these instruments for inclusion in Tier 1 capital.[6] Such instruments were subject to stringent conditions (such as being permanent; being junior to depositors, general creditors and subordinated debt of the bank; able to absorb losses within the bank on a going-concern basis; callable at the initiative of the issuer only after a minimum of five years with supervisory approval; and under the condition that it would be replaced with capital of the same or better quality) and limited to a maximum of 15 percent of Tier 1 capital. Any extra could be counted toward Tier 2 capital. Thus, innovative capital instruments are also known as Lower Tier 1, as opposed to Upper Tier 1 for the other components.

The other elements of capital (supplementary capital) are admitted into Tier 2 but are limited to 100 percent of Tier 1 and are subject to certain conditions. Each of these elements might or might not be included by national authorities at their discretion in the light of their national accounting and supervisory regulations.

In 1996, Tier 3 capital was introduced only as coverage for market risk. In fact, at the discretion of their national authority, banks can also use a third tier of capital that consists of short-term subordinated debt for the sole purpose of meeting a proportion of the capital requirements for market risks (BCBS, 1996).

2.1.2. Risk-weighted assets

The denominator of the capital ratio is the risk-weighted assets, which are a measure of the amount of a bank’s assets (and off-balance-sheet exposures) adjusted for risk. The underlying

[4] Issued and fully paid ordinary shares/common stock and perpetual noncumulative preference shares

[5] Reserves created or increased by appropriations of retained earnings or other surplus, e.g. share premiums, retained profit, general reserves, and legal reserves.

[6] The definition of eligible regulatory capital was clarified in the October 27,1998, press release on “Instruments eligible for inclusion in Tier 1 capital.”

rationale is that banks' assets have different risk profiles and that riskier assets require higher amounts of capital. The Basel Committee designed a system of risk weights (0 percent, 20 percent, 50 percent, and 100 percent) to measure the riskiness of banks' assets. Assets are assigned to one of those four risk weights on the basis of their features (debtor type, debtor's country of residence, and asset type). Thus, assets considered to be riskier are assigned to a higher weight.

Before being assigned to the appropriate risk-weighted categories, offbalance sheet exposures are converted to loan equivalent exposures on the basis of rules that predict the likelihood of actual credit exposure.

Table 1: Components of regulatory capital in the Basel Accord

Component			Limits and restrictions
TIER 1	*Upper* Tier 1	Paid-up share capital / common stock	At least 4 percent of RWA
		Disclosed reserves (e.g., retained earnings and share premium reserves)	
	Lower Tier 1	Innovative capital instruments	No more than 15 percent of T1
TIER 2	*Upper* Tier 2	Undisclosed reserves	No more than 100 percent of T1
		Revaluation reserves	
		General provisions / general loan- loss reserves	
		Hybrid (debt / equity) capital instruments	
	Lower Tier 2	Subordinated term debt	No more than 50 percent of T1
TIER 3	Short-term subordinated debt covering market risks		No more than 250 percent of T1 for market risk
Deductions	Goodwill		Deducted from T1
	Investments in nonconsolidated banks and financial institutions		Deducted 50 percent from T1 and 50 percent from T2 capital

Basel I's fundamental objectives were to promote the soundness and stability of the international banking system and to provide a level playing field for international competition among banks. In particular, Basel I played a major role in reversing the gradual decrease in the capitalization of the most advanced banking systems: the capital to total assets ratio gradually declined from about 15–20 percent at the beginning of the 20th century to less than 10 percent in the 1970s.

After 1988, the average capital ratio of major banks in developed countries steadily increased. This increase reflected not only the direct effect of Basel I, but also improved market discipline, because the introduction of consistent standards for banks worked to increase transparency and improved the market's ability to exert pressure. Moreover, Basel I has effectively contributed to reducing competitive inequality among banks in different countries.[7]

2.1.3. Basel I limits

Notwithstanding its merits, inherent in Basel I are some flaws that affected the effectiveness of the overall capital framework as time went by. The most relevant limitations are the following:

A. Recognition of a single source of risk

Basel I focuses on credit risk only. Other relevant sources of risks, namely interest rate risk, market risk, and operational risk, are ignored. Only in 1996 did the Committees amend the Accord to extend capital requirements to market risk.

B. Limited differentiation of risk

Basel I is based on only a limited differentiation of risk that uses a broad category of exposure with an 8 percent charge for all exposures except OECD governments,[8] OECD interbanks, under one-year non OECD interbanks, and residential mortgages. The requirements mainly reflect the type of borrower and not the riskiness of the loan (except for the OECD/non-OECD distinction

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[7] One of the main concerns of the banking international community was the advantage of Japanese banks that operated with an apparently lower capital to total assets ratio than their competitors in developed countries (G-10). The latter, especially British and US banks during the 1980s, had gradually lost shares of the international bank loans market. Analysis of the impact of the 1988 Accord on international banks showed that the average capital to total assets of Japanese banks was 2.1 percent, versus 3.3 percent for Germany, 4.9 percent for the USA, 5.1 percent for Canada, 5.4 percent for the UK, and 6.3 percent for Switzerland. However, including undisclosed reserves, Japan's ratio increased to 12.4 percent.

[8] The OECD group comprises, for the purpose of the 1988 Accord, all members of the OECD or countries that have concluded special lending arrangements with the International Monetary Fund that are associated with the Fund's General Arrangements to Borrow, and which have not rescheduled their external sovereign debt within the previous five years.

and the recognition of some types of financial collateral) and therefore do not change if the creditworthiness of borrowers deteriorates. Thus, all private borrowers are rated as equally risky, and companies with different ratings are required to meet the same capital requirements. By the same token, all loans to non-OECD countries are rated as riskier than loans to OECD countries, regardless of their respective ratings.[9]

C. Inadequate consideration of the relation between borrower risk and loan maturity

Despite the fact that loans with a longer maturity (life horizon) are riskier, Basel I only considers to a very limited extent the link between maturity and credit risk. In fact, only some short-term exposures (off-balance sheet exposures and interbank loans) are required to face lower capital requirements.

D. Neglect of loan portfolio diversification benefits

Basel I does not reward banks that reduce their systematic risk, because no recognition is given for risk diversification of a bank's loan portfolio. If portfolios with a high number of well diversified loans require the same level of capital as portfolios heavily concentrated on just a few borrowers, industries, or geographies, then banks do not have any incentive to diversify credit risk. Moreover, the limitations of Basel I widens the gap between regulatory capital and the measures of capital at risk that banks estimate according to internal models. Banks are encouraged to engage in regulatory arbitrage to exploit such differences. The typical transaction is a securitization of assets that have a high risk weighting. Banks can either cherrypick safe assets to sell, or securitize on terms such that default risk is not transferred but merely taken off the balance sheet. Regulatory arbitrage can also transform how assets are treated (for example, securities with a high credit rating can have a lower risk weighting than the assets backing them). This means that the capital requirement for the banking system as a whole can fall even though the same risks are being absorbed, leading to an increase in systemic risk.

2.2.The new Capital Accord (Basel II)

[9] When this approach was adopted, the Basel Committee recognized the shortcoming that some countries might not merit inclusion on grounds strictly related to default risk, but might be included in the preferential group while potentially high credit quality countries outside the OECD might be excluded. However, when adopted, the OECD/non-OECD approach was determined to be the most workable proxy for identifying countries that should be eligible for preferential risk-weighting treatment.

2.2.1. General features

In response to the criticism of Basel I, the BCBS worked to amend and complete the original framework. In 1996, it issued an amendment to extend the regulatory capital requirements to market risks that allowed banks to use their internal models for regulatory purposes, subject to the approval of the supervisory authority. In 1999, the BCBS began an extensive review of credit risk requirements and addressed the issue of operational risk. A number of changes were made that culminated in the 2001 proposal (BCBS, 2001). Over 250 comments from banks, together with the Committee's three impact studies, resulted in substantial changes to the original document. A final consultative document was published in April 2003, and the final version of the new Capital Accord (Basel II) was released in June 2004 (BCBS, 2004).

Basel I's fundamental objectives were to ensure the solvency of the banking system and the consistency of internationally competitive conditions. Basel II set forth a new objective, by promoting capital requirements more sensitive to the underlying risk of the assets, thus narrowing the gap between regulatory capital and the internal capital that banks measure. To this aim, capital requirements were extended to a broader range of risk (credit; market; and, for the first time ever, operational risks), and the capital requirements' calculation rules were improved to better reflect the risk of the underlying positions. Moreover, Basel II emphasizes the roles of both the supervisory process aimed at reviewing and assessing supervised banks' overall capital adequacy and of the market to discipline banks' behavior.

Thus, Basel II consists of three mutually reinforcing pillars: Pillar 1, that sets new, more precise, rules for calculating minimum capital requirements for credit, market, and operational risks; Pillar 2, that provides guidelines aimed at reinforcing the internal governance and risk management of banks and at developing an intensive interaction between supervisors and banks; and Pillar 3, that establishes core disclosure by banks in order to improve market discipline.

2.2.2. Changes from Basel I

In practice, Basel II affirms that minimum capital levels, though calculated more accurately, are not enough to fulfill supervisory goals: in an increasingly complex environment, capital adequacy cannot be assessed without taking into consideration the functioning and the reliability of the firm's risk management system. Equally important is the disciplinary function that market participants – investors, rating agencies and financial analysts – can perform.

With respect to Basel I, **Pillar 1** of Basel II was not a novelty: banks are required to maintain a minimum capital level to support risk taking; the minimum level of the ratio of capital to risk-weighted assets is kept at 8 percent; different weightings are assigned to various types of assets with different risk profiles. What changed were the risk categories that banks must consider, and the rules for calculating capital requirements.

The new capital requirements are not limited to credit risks. In Basel II, a new capital requirement is introduced to operational risks, whereas capital charges on market risk are still calculated according to the guidelines set in 1996.

The market risk capital rules were recently amended to tackle the problems that emerged during the financial crisis. One of the most relevant innovations of Basel II is the system of alternative rules for calculating the minimum capital requirements. In particular, with respect to Basel I, rules for calculating the denominator of the capital ratio have been profoundly modified, while the minimum level that banks must hold (8 percent) and the numerator definition have not.

$$\text{Capital Ratio}_{\text{Basel 2}} = \frac{\text{Regulatory Capital}}{\text{RWA}_{\text{Credit risk}} + 12,5^{*}\text{K}_{\text{Market risk}} + 12,5^{*}\text{K}_{\text{Operational risk}}} \geq 8\%$$

The denominator is the sum of the assets weighted by risk: assets weighted by credit risk are directly computed; but for market and operational risks, the capital requirement is multiplied by 12.5 (the reciprocal of 8 percent) to ensure consistency in calculating the overall denominator.

For each risk type, banks can choose among different methods that range from a simplified approach to one or more internal methods that are increasingly complex but are also more accurate. Basel II offers economic incentives for banks to adopt more sophisticated approaches and hence to improve their risk and capital management practices. Table 2 below illustrates the possible approaches.

Table 2: Pillar 1 approaches for the calculation of minimum capital

Credit risk	Counterparty risk	Market risk	Operational risk
Standardized	Current exposure method	Standardized	Basic Indicator Approach
IRB Foundation	Standardized	Internal models	Standardized
IRB Advanced	Internal model (EPE)		Internal model (AMA)

As for credit risk, in contrast to Basel I, loans extended to similar borrowers are subject to different regulatory capital requirements depending on their specific riskiness. In fact, Basel II permits banks a choice between two broad methods for calculating their capital requirements for credit risk. One alternative, the standardized approach, is to measure credit risk in a standardized manner supported by external credit assessments. The other alternative, the internal ratings-based (IRB) approach, is subject to the explicit approval of the bank's supervisor and allows banks to use their internal rating systems for credit risk.

Under the IRB approach, two broad methods are available: foundation and advanced. Under the foundation method, as a general rule, banks provide their own estimates of the probability of default (PD) for borrowers and rely on supervisory estimates for other risk components, the levels of losses, and exposures at the time of default, namely the loss given at default (LGD) and the Exposure at Default (EAD). Under the advanced method, the banks provide more of their own estimates of the PD, LGD, and EAD, and their own calculation of the maturity of the loans (M), subject to meeting minimum standards.

Rules introduced in 1996 for calculating capital requirements for market risks have not significantly changed with reference to calculation methods: banks can choose between a standardized system and an internal model for risk measurement. To be accepted for regulatory purposes, the internal models have to conform to some minimum requirements and are subject to supervisory approval.

The definition of operational risk is "the risk of loss resulting from inadequate or failed internal processes, people and systems, or from external events". Basel II presents three methods, in a continuum of increasing sophistication and risk sensitivity, for calculating the capital charges from operational risk: the basic indicator approach; the standardized approach; and the Advanced Measurement Approach (AMA).

Banks that use the basic indicator approach must hold capital for operational risk equal to the average over the previous three years of a fixed percentage (15 percent) of positive annual gross income.

In the standardized approach, bank activities are divided into eight business lines. Within each business line, gross income is a broad indicator that serves as a proxy for the scale of business operations and thus the likely scale of operational risk exposure within each of these business lines. The capital charge for each business line is calculated by multiplying gross income by a factor assigned to that business line. Each factor serves as a proxy for the industry-wide relation between the operational risk-loss experience for a given business line and the aggregate level of gross income for that business line. The total capital charge is calculated as the three-year average of the simple sum of the regulatory capital charges across each of the business lines in each year. Under the AMA approach, the regulatory capital requirement equals the risk measure generated by the bank's internal risk measurement system. Use of the AMA is subject to supervisory approval.

Pillar 2 requires banks to adopt a process for assessing their overall capital adequacy in relation to their risk profile and a strategy for maintaining their capital levels. Also the risks not adequately covered under Pillar 1 (such as credit concentration and correlation) and the risks not in Pillar 1 at all (such as interest rate risk on the banking book) have to be considered in the Pillar 2 framework. Moreover, banks must also carefully monitor the effect played by some bank-external factors (such as the economic cycle), even developing suitable stress-testing methods and tools.

Against this backdrop, supervisory authorities expect banks to operate with an amount of capital in excess of the minimum requirements, and they can request banks to hold a higher amount of capital than the minimum requirement. To this end, supervisory authorities perform an overall review of the risk and capital management processes carried out by the individual banks that aim at evaluating processes, techniques, and strategies to calculate and maintain adequate capital levels. The supervisory review process enables authorities to promptly intervene in order to avoid capital falling below the minimum requirement.

Pillar 2 focuses on this supervisory review process. In fact, the banks' internal risk measurement systems are recognized as more accurate and more closely tailored to the specific risk profile of each individual bank than the universal Pillar 1 system. However, the assessment of the full reliability of such banks' internal processes requires an intensive interaction between the supervisory authorities and the banks.

The principle underlying **Pillar 3** is that market discipline can play an effective role in assessing banks' financial conditions and thus complement the minimum capital requirements (Pillar 1) and the supervisory review process (Pillar 2) if market participants have reliable, detailed and prompt information on risks and capital. To this end, Basel II encourages market discipline by defining a set of disclosure requirements that allows market participants to assess key pieces of information on capital, risk exposures, risk assessment processes, and hence the capital adequacy of each individual institution. Banks that adopt more advanced approaches to calculate capital requirements are required to comply with stricter disclosure criteria.

The standardized approaches were to be adopted by the G-10 countries' banks by the end of 2006, and the advanced approaches were to take effect at the end of 2007. During the first year of implementation, banks and national regulators were expected to run parallel calculations that computed capital requirements based on Basel I and Basel II.

2.3.Basel III

2.3.1. Changes from Basel II

Basel II revises signifcantly the Basel Accord, so called Basel I (BCBS, "International Convergence of Capital Measurement and Capital Standards", July 1988), by creating an international standard for banks as well as regulators. It was expected to be implemented before but it has never been fully completed because of the fnancial crisis of 2007–2008, and thus the emerging of Basel III. To some extent, Basel III is merely a revision of the Basel II framework but current regulatory risk management businesses have been largely shifted to implement Basel III and some other regulatory modifcations on the global systemically important banks. It is worth mentioning that each jurisdiction has its own right to make adjustment for its domestic fnancial frms within the Basel III framework.

There are four major changes from Basel II to Basel III, which will be in full effect by 2023:

2.3.1.1. *Capital requirement*

A. A global standard and transparent defnition of regular capital. Some capitals (for instance Tier 3 and some Tier 2 capitals) in Basel II are no longer treated as capitals in Basel III.

B. Increased overall capital requirement. Between 2013 and 2019, the common equity Tier 1 capital increases from 2% in Basel II of a bank's risk-weighted assets *before* certain regulatory deductions to 4.5% *after* such deduction in Basel III.

C. The total capital requirement (Tier 1 and Tier 2) increases from 8% in Basel II to 10.5% in Basel III by January 2009. Some jurisdictions can require even higher capital ratios.

D. A new 2.5% capital conservation buffer is introduced and implemented by January 2019.

E. A new zero to 2.5% countercyclical capital buffer is introduced and implemented by January 2019.

2.3.1.2. *Enhancing the risk coverage in the capital framework*

A. Resecuritization exposures and certain liquidity commitments held in the banking book require more capital.

B. In the trading book, banks are subject to new "stressed value-at-risk" models, increased counterparty risk charge, increased charges for exposures to other fnancial institutions and increased charges for securitization exposures.

2.3.1.3. *New leverage ratio*

A. Introduce a new leverage ratio that measures against a bank's total exposure, not risk-weighted, including both on and off balance sheet activities.

$$\text{Basel III Leverage Ratio (\%)} = \frac{\text{Tier 1 Capital}}{\text{Exposure Measure}} \geq 3\%$$

B. Implementation of the minimal leverage ratio will be adopted in January 2019.

C. An extra layer of protection against the model risk and measurement risk.

2.3.1.4. *TwoNew liquidity ratios*

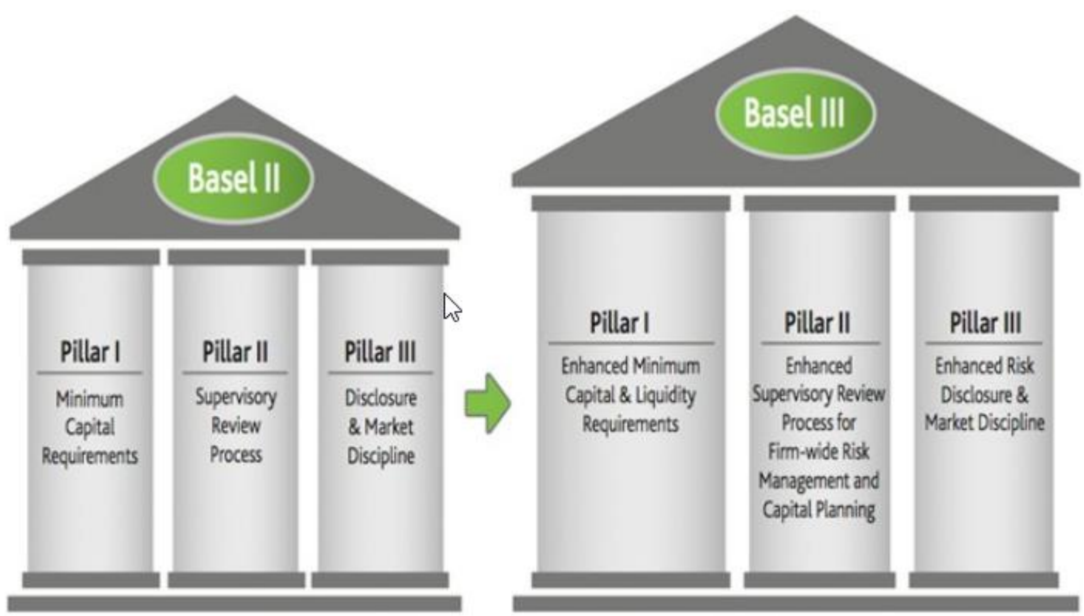
A. A "Liquidity coverage ratio" (LCR) requiring high-quality liquid assets to equal or exceed high-stressed one-month cash flows has been adopted from 2015.

$$LCR = \frac{\text{High quality liquid asset amount (HQLA)}}{\text{Total net cash flow amount}} \geq 100\%$$

B. A "Net stable funding ratio" (NSFR) requiring available stable funding to equal or exceed required stable funding over a one-year period will be adopted from January 2018.

$$\frac{\text{Available amount of stable funding}}{\text{Required amount of stable funding}} \geq 100\%$$

Figure 2: Transition for Basel ll to Basel lll



2.3.2. Capital In Basel III

Capitals in Basel III is divided into two categories: **Tier 1 capital** (going concern capital) and **Tier 2 capital** (gone-concern capital). One purpose of a global capital standard is to address the inconsistency in the defnition of capital across different jurisdictions and the lack of disclosure that would have enabled the market to fully assess and compare the quality of capital across jurisdictions.

Comparing with the capital defnition in Basel II, the quality, consistency, and the transparency of the capital base is raised signifcantly. Briefly, the predominant form of Tier 1 capital must be common equity and retained earnings; Tier 2 capital instruments are harmonized and original Tier 3 capitals in Basel II are eliminated completely. In addition, Basel III primarily focuses on high quality capital—common equity—given its highest loss-absorbing ability.

2.3.2.1 Tier 1 Capital

Specifcally, Tier 1 capital is either common equity Tier 1 capital (CET 1) or additional Tier 1 capital.

a. Common Equity Tier 1 Capital

Common equity Tier 1 capital is largely common shares issued by the bank and retained earnings plus common shares issued by consolidated subsidiaries of the bank and held by third parties (minority interest) that meet the criteria for classifcation as common shares for regulatory capital purposes. Moreover, regulatory adjustments have to be applied in the calculation of common equity Tier 1.

There are 14 criteria for classifcation as common shares for regulatory capital purposes[10], the main ones being as follows:

1- It is entitled to a claim on the residual assets that is proportional with its share of issued capital;
2- It must be the most subordinated claim in liquidation of the bank;
3- Its principal is perpetual and never repaid outside of liquidation;

[10] BCBS, June 2011, pp. 14–15

4- The bank does nothing to create an expectation at issuance that the instrument will be bought back, redeemed, or cancelled.
5- Lastly, the distributions are paid out of distributed items and distributions are never obligated and paid only after all legal and contractual obligations to all more senior capital instruments are resolved; these instruments are loss-absorbing on a going-concern basis, and the paid in amount is recognized as capital (but not as liability) for determining balance sheet insolvency.

b. Additional Tier 1 Capital

Besides common equity Tier 1, there is additional Tier 1 capital within the Tier 1 capital category. Additional Tier 1 capital includes the instruments issued by the bank that meet the criteria for inclusion in additional Tier 1 capital and stock surplus (share premium) resulting from the issue of instruments (including that issued by consolidated subsidiaries of the bank and held by third parties) included in additional Tier 1 capital.

2.3.2.2. Tier 2 Capital

Tier 2 capital is a gone-concern capital and its criteria has been revised through several versions[11].

Specifcally, Tier 2 capital consists of instruments issued by the bank, or consolidated subsidiaries of the bank and held by third parties, that meet the criteria for inclusion in Tier 2 capital or the stock surplus (share premium) resulting from the issue of instruments included in Tier 2 capital.

Since the objective of Tier 2 capital is to provide loss absorption on a gone-concern basis, the following set of criteria for an instrument to meet or exceed is stated precisely in BCBS, June 2011: The instrument must be issued and paid-in, subordinated to depositors and general creditors of the bank. Maturity is at least fve years and recognition in regulatory capital in the remaining fve years before maturity will be amortized on a straight-line basis; and there are no step-ups or other incentives to redeem. It may be called after a minimum of five years with supervisory approval but the bank does not create an expectation that the call will be exercised.

[11] BCBS, "Proposal to ensure the loss absorbency of regulatory capital at the point of non-viability", August 2010)

Moreover, banks must not call the exercise option unless it

1- demonstrates that this capital position is well above the minimum capital requirement after the call option is exercised, or
2- banks replace the called instrument with capital of the same or better quality and the replacement of this capital is done at conditions which are sustainable for the income capacity of the bank. The dividend/coupon payment is not credit sensitive.

Furthermore, the investor has no option to accelerate the repayment of future scheduled payments (either coupon/dividend or principal) except in bankruptcy and liquidation.

2.4.Regulatory Framework in Algeria

The new prudential regulations applicable to banks and financial institutions as from October 2014 constitute a structuring reform for the Algerian banking sector which is now robust, judging by the assessment made by multilateral financial institutions.

With respect to regulations enacted in 1994-1995 and in 2007, the new prudential regulations cover not only credit risk but also operational and market risks. These are regulation 14-01 relating to solvency ratios applicable to banks and financial institution, regulation 14-02 relating to large exposures and shareholding and regulation 14-03 relating to the ranking and provisioning of claims and commitments by signature. The economics of this new prudential framework shall be explained through a succinct presentation of these three regulations.

2.4.1. Regulation 14-01 relating to solvency ratios: defines core capital and additional equity capital by including the overall recommendations in this area under the so-called Basel II standards.

In termbs of core capital relative to the definition contained in the regulations issued in 1994, two deductions are required: the deduction for exceeding limits of shareholding set in regulation 14-02 is to be done on core capital, while total shareholding in banks and financial institutions (for which there are no standard levels) is to be deducted as follows: 50% from core capital and the remaining 50% is to be deducted from the additional equity capital. The previous regulations did not provide for the first deduction, while the second deduction applied to 100% of the shareholding in banks and financial institutions.

The new definition of core capital incorporates elements that may be included at intermediate periods. These elements are the same as the ones included in the previous regulation, namely: statement of income approved by auditors and validated by the Banking Commission calculated after deduction of all expenses incurred in the period and depreciation and amortization expenses and provisions, calculated net of corporate income tax and advance payments on dividends.

As to additional equity capital, they include only 50% of revaluation differentials and unrealized gains arising from the fair value valuation of assets available for sale and only 1.25% of total risks in respect of provisions constituted to cover general banking risks (excluding regulated provisions of 5% on medium and long term credits as part of core capital). Furthermore, as in the previous regulation, additional equity capital may be taken into consideration only within the limit of core capital and subordinated loans may be included in additional equity capital only within the limit of 50% of core capital.

The solvency ratio (regulatory equity capital over risks incurred on credit risks, operational risks and market risks) is raised to 9.5% versus 8% earlier. Unlike the previous regulation, a solvency ratio for core capital is introduced and fixed at the level of 7% of total risks. In addition, a safety cushion in core capital is implemented and covers 2.5% of weighted risks.

The new regulations provide the possibility for the Banking Commission to require banks and financial institutions of systemic importance higher standards of solvency ratios to those imposed. Moreover, in case of non-compliance with solvency ratios, the Banking Commission may impose deadlines on banks and financial institutions concerned for compliance with the requirements in this area, as well as restrictions on the distribution of dividends in the case of nonconstitution or insufficient constitution of core capital with regard to safety cushion.

Credit risks incurred are redesigned by using, depending on the nature and quality of the counterparty, ratings assigned by external credit assessment institutions whose list shall be decided upon by the Banking Commission or in the absence of rating, the standard weights provided for.

The new regulations provide weighting benefits for credits to small enterprises (weighting of 75% under certain conditions), for residential mortgage loans (weighting of 35% under certain conditions), and mortgage loans for commercial use (weighting of 75% under certain conditions), whereas the previous regulations provided the possibility of a weighting of 50% of mortgage loans only. In addition, particular larger weightings are provided for nonperforming loans, that is to say with regard on the level of provisioning constituted, contrary to the previous regulations.

Securities loaned or sold under repurchase agreements are weighted according to the quality of the issuer, while the previous regulations did not specify this component.

Quantum conversion of credit risk for commitments by signature have not been altered in the new regulations due to the fact that local banks do not make conditional and / or derivatives operations that have entries in the off balance sheet statement. Financial guarantees as a factor of risk reduction have been specified, namely the conditions of their admission and their weighting has been further refined. This was not explained in detail in the previous regulations.

The definition of operational risks measurements (15% of net banking income over the average of the last three fiscal balance sheets) and market risks (position risk on the trading book minus general and specific risks and minus exchange risk) is that of the basic method of Basel II with quantum evaluation of regulatory equity capital and integration of this quantum in the overall formula for calculating the solvency ratio of regulatory equity capital. Those risks were not regulated.

Finally, the new regulations regarding solvency ratios introduce for the benefit of banks and financial institutions, some elements of prudential supervision relating to the adequacy of equity capital to risks and some elements of financial communication. The monitoring system must be documented and reviewed regularly, allowing periodic reporting to the legislative body and the executive body. Prudential supervision is also requested through the conduct of stress tests to assess the vulnerability of loans portfolio in case of an economic downturn or deterioration in the quality of counterparties. As regards financial communication, the establishment of a formalized procedure for financial communication is also requested and shall be approved by the governing body, in compliance with legal and regulatory provisions in force.

2.4.2. Regulation 14-02 relating to major risks and shareholdings: defines "major risk" as total risk incurred on same beneficiary as a result of these operations whose amount exceeds 10% of the regulatory equity capital of the bank or the financial institution concerned. It defines “related persons” as natural persons or legal entities that have ties of such nature that it is likely that the difficulties of funding or repaying of loans experienced by one person affect the other persons. As to “shareholdings", these are securities whose term ownership enables to exert an influence or control over the issuing company, which is deemed to exist only if the shareholding is of at least 10% of the capital or the voting rights of the company concerned. A "same beneficiary" is a natural person, a legal entity or related persons upon which the bank or the financial institution incurs a risk.

Standard risk division is the same as in the previous regulations, namely a maximum ratio of 25% between the net weighted overall credit risks that a bank or a financial institution incurs on a same beneficiary and the amount of regulatory equity capital. In the new regulations the concept of beneficiary or group is better defined. However, the Banking Commission may require for some beneficiaries or for all beneficiaries of a bank or financial institution a maximum ratio lower than this threshold.

The total major risks is limited to eight (8) times the amount of regulatory equity capital of the bank or financial institution concerned, corresponding to a tightening of the standard risk as compared to the previous regulations

Exceeding the standards set for large personal risk at 25% of total equity capital and for total major risks at 60% of regulatory equity capital shall, unlike the previous regulations, be subject to sanctions by the Banking Commission. As regards total credit risks on a beneficiary, it is defined as in the previous regulations, as balance sheet and off-balance sheet credit exposures.

Financial guarantees admitted to be deducted from major risks are the financial guarantees accepted in respect of credit risk as defined in Regulation 14-01, but possibility is given to deduct from residential real estate loans 50% of the asset concerned pledged under certain conditions. Weighting ratios of credit risks for the purpose of assessing large risks are identified depending on the nature of the debts and do not take into account external ratings of credits on residents; off-balance sheet risks being assessed in equivalent credit risks by applying conversion factors. Banks and financial institutions are compelled to have an external audit report on beneficiaries falling into the category of "major risk".

Standard shareholdings of banks and financial institutions are individually set at 15% of regulatory equity capital and at 60% for all of shareholdings. Shareholdings in banks and financial institution based in Algeria shall not be subject to standard levels due to the fact that these shareholdings are deducted from equity (50% from core capital and 50% from additional equity capital). The same applies for shareholdings in companies under Algerian Law that constitute a division or continuation of banking activity, including real estate development companies set up by banks and financial institutions and companies that manage local interbank services.

2.4.3. Regulation 14-03 relating to classification and provisioning of claims and commitments by signature of banks and financial institutions: redefines all of the components of classification and provisioning of claims and commitments by signature and their methods of accounting as compared to the regulations of 1994.

Claims are represented by credits granted to natural persons or legal entities and recorded in the balance sheet of banks and financial institutions. These claims are either ongoing or classified as uncollectible. Ongoing claims are those for which full collection within the contractual deadline seems assured. Shall be included among ongoing claims, those that do not meet the definition of ongoing claims above but which are coupled with the guarantee of the State; with guarantees in the form of deposits lodged with the lending bank or financial institution; or with secured pledged securities that can be settled without their value being affected. Indeed, these are claims that are not subject to the provisioning provided for claims classified as uncollectible.

Claims classified as uncollectible fall into three categories. With respect to the previous regulations, the elements of assessment and ranking are more detailed in this new regulation. The elements of assessment include information relating to the deteriorating financial position of the counterparty, namely the significant decrease in turnover, the excessive indebtedness and internal difficulties such as shareholder disputes. The new regulation supports the requirements for the classification of leases and secured personal mortgage loans, which were not expressly provided for in the previous regulations.

Downgrading of a claim entails, via contagion effect, the downgrading of all other claims on same counterparty, toward the same category of classified claims, as well as the downgrading of commitments by signature. If the counterparty belongs to a group, the assessment is made of the impact of the failure of this counterparty on the situation of the group, and if necessary, the downgrading of all claims on group entities is made.

In case of restructuring classified claims, these are to be maintained in the category of classified claims for a period of at least twelve (12) months. After this period, reclassification into ongoing claims may be considered, provided that the new repayment schedule is respected and the interests thereon are effectively received. The list of classified claims that have been subject to at least a restructuring and whose amount is over 50 million dinars must be notified quarterly to the Banking Commission and to Bank of Algeria.

Claims classified as uncollectible, that is to say those for which there is no prospect of collection, should be written off only after exhausting all amicable or judicial means, except for small claims that may be directly written off, considering the amount of litigation costs.

With regard to provisioning, the resulting percentages in the new regulation of 20%, 50% and 100% respectively for the three categories of classified claims, are revised compared to those in the previous regulation. Provisioning is performed on gross amount (excluding uncollected interests) net of collateral accepted. The latter and the threshold of deductions are however more clearly specified in this regulation than in the previous.

In case of failure to implement real guarantees within a five (5) years period as from the first downgrading of the claim concerned, the latter must be funded in full without deduction of such guarantees. Banks and financial institutions must have internal procedures such as to enable them to ensure the legal validity of the collateral received, verify casualty insurance underwritten and assess the amount of coverage actually offered and the ability of effective and prompt implementation of the collateral.

Examination of the ranking of claims must be made at least quarterly. The quality of collateral received, in particular with respect to market value and the ability to implement them needs to be reviewed at least annually.

The method of accounting for non-performing loans is specified in light of new accounting standards implemented for banks and financial institutions as of January 2010.

Interests due on outstanding non-performing loans are not to be charged to the profit and loss account as in the previous regulation. Accrued interests but not yet due resulting are thus respectively charged to the debit of the appropriate account of related receivables and to the credit of appropriate accounts of related debts.

Section 3: Evolution of credit risk measurement models

Most often, we define credit risk as the risk of losses due to defaults on loans to borrowers. It is the case, when the other party in a financial transaction will not behave in accordance with the terms and conditions of contract, causing financial loss to the holder of assets. However, exposure to credit risk arises in the whole range of bank's activities, not only in providing loans, for example, during the process of issuing loan commitments and guarantees in bankers' acceptances, in trading on the capital market when dealing with foreign exchanges, futures, swaps, bonds, options, stocks, etc.

Difficulties in credit risk modelling arise from the fact that business bankruptcies (defaults) are not a frequent phenomenon but occur mainly unexpectedly. However, if default occurs, in fact, it often causes major losses to lenders or creditors, but we do not know how to quantify their size in advance. Approach of individual authors to this issue is diverse and so is the methodology that is used for this purpose.

So, credit risk has many different forms and companies manage it in various ways. Decades ago, experts used subjective decision for evaluating potential borrowers and their requests. Their judgment relied for example on reputation, capital, volatility, collateral and trading was mainly driven by interest rate risk.

The problem with this method is the absence of a uniform, objective rating algorithm and the high costs associated with maintaining experts. In addition, if an expert makes a mistake, then the company loses money due to an underestimation of the risk or losing profit opportunities due to its overestimation. As a result, most of the subjects does not have their own credit analysts, but rely on the results of the work of rating agencies.

3.1.Rating agencies– era without models

First help came from ratings agencies. Firstly in 1900 John Moody and Company introduced "Moody's Manual of Industrial and Miscellaneous Securities". The book published basic statistics and general information about stocks, shares and bonds of various industries. Moody's began introducing bond ratings in 1909 for U.S. railroads and in 1924 Moody's ratings contained nearly 100% of the market of US bond.

Henry Varnum Poor was the first to publish the "History of Railroads and Canals in the United States" in 1860,the forerunner security study and reporting was developed over the next century. Poor's Publishing Co. and Standard Statistics (formed 1906, in 1941 merged to Standard & Poor's) started rating bonds in 1922.
In 1913 the Fitch Publishing Company was founded. Fitch developed financial statistics which is for the usage in the industry of investment via "The Fitch Stock and Bond Manual" and "The Fitch Bond Book." In 1924, Fitch published the AAA through D rating system that has become the base for ratings throughout the industry, later accepted and certified by S&P. Alike S&P, Fitch also uses middle +/- transformers for each group between AA and CCC (e.g., AA+, AA, AA-, A+, A, A-, BBB+, BBB, BBB-, etc.), which is used also by Moody's with a comparable measure.

3.2.First mathematical models

The first works devoted to default predication models made Beaver in 1967 and Altman in 1968.They are suggested first scoring models using set of accounting and market values. The Altman's Z – score is a linear combination of five joint business ratios, weighted by coefficients. The coefficients were valued by classifying a set of companies which had confirmed bankruptcy and then gathering a harmonized example of companies which had survived, with corresponding by industry and approximate size (assets).For example, a Z – Score above 3.0 indicates financial soundness; below 1.8 suggests a high likelihood of bankruptcy. Altman´s analysis illustrated on a harmonized example covering 66 manufacturing firms (33 failed and 33 non-failed) during the period 1946-1965.

In 1977,Altman, Halde man and Narayanan created improved model (ZETA) with numerousim provements to the original Z – Score model. Additionally new model was focused on bigger companies with an average of $100 million. In 2005 Altman and Sabato have constructed a Z – Score – type model for SME (small and medium sized enterprises). This model uses facts on 120 defaults and 1,890 non defaults through the period 1994–2002.[12]

The advantage of Altman approach is its easy applicabilityin practice but it has also drawn several statistical objections over the years. This model lack seconomic just ification, the result is only of statistical analysis and the model uses unadjusted accounting data.

In 2000 was introduced Moody's KMV RiskCalc. This model is based on financial ratios like the Z – Score and ZETA models, but it used significantly larger database Z-Score models. Over 1.5 million companies and close to 100,000 default events through the world. The way in which are presented the ratios to the model is also different: transformed values of the variable indicative of the ranking within the population are used rather than raw values.

3.3.First generation structural-form models

In 1974, Merton published model that is considered the first structural model. This model is based on ideas of option pricing by Black and Scholes from 1973.[13]In this approach, a firm will default when on the maturity of its debt its value of the market is lower than the value of its liabilities. Merton derived a clear for mulation for risky bonds which can be used equally to evaluate the probability of default of a company and to evaluate the credit spread.

In Merton's theoretical framework all of the related credit risk components, containing default and recovery at default, are a function of the structural characteristics of the company and probability of default (PD) and recovery rate (RR) are inversely connected. If the value of the company increases, then its PD tends to decrease while the expected RR at default increases (ceteris paribus). On the other hand if the company´s debt increases, its PD increases while the expected RR at default decreases. Lastly, if the company´s asset volatility increases, its PD increases while the expected RR at default decreases.

[12] J. B. Caouette et al, Managing credit risk: The great challenge for global financial markets, 2nd Edition,*New York: Wiley Finance*, pp.627, 2008.
[13] R. Merton, On the Pricing of Corporate Debt: The Risk Structure of Interest Rate, *Journal of Finance*, vol. 29, pp. 449–470, 1974.

Structural models depend on on the idea of distance – to – default. This theory is a standardized measure of the variance between the asset of the company and liability values.

Very soon appeared models with aim improve the original Merton framework by reducing some of his assumptions. Geske modifies the original Merton framework by allowing the risky bond to have discrete interest payments in 1977. [14]In 1976, Black and Cox published similar problem, but only for interest payments. Black and Cox also worked on the case where defaults happen immediately when value of the asset of the company falls under a positive threshold. In 1984 Vasicek found a method to find the price of a short-term loan. [15]

3.4.Second generation structural-form models

In the original Merton model the company defaults at the time of maturity of the debt, also this model assumes a flat risk-free term structure. However, these assumptions are often unrealistic. In 1993,Kim, Ram aswamy and Sundaresan presented model where default might happen anytime amongst the issuance and maturity of the bond and they relaxed the flat risk-free rate assumption by identifying a stochastic progression for the evolution of the short rate. [16]

Long staff and Schwartz showed that connection among default risk and the interest rate has animportant consequence on the goods of the credit spread in 1995. [17]

The main problem of structural models is that they are not consistent with the risk – neutral probability of default and the company´s asset value and their volatility are not every time observable characteristics. These models do not take into account credit – rating changes for risky corporate debt of the firms. So the second generation structural – form models cannot be used to price numerous credit derivatives whose payouts depend on the credit rating of the debt issue. In second generation structural-form models, the RR is exogenous and independent from the asset value of the company. RR is independent from the PD because RR is usually defined as a fixed ratio of the remaining debt value.

[14] R. Geske, The Valuation of Corporate Liabilities as Compound Options, *Journal of Financial and Quantitative Analysis*, vol. 12, no.4, pp. 541-552, 1977.

[15] O. A. Vasicek, Credit Valuation.*San Francisco: Moody's KMV Corporation*, 1984

[16] I.J.Kim, K. Ramaswamy and S. Sundaresan. Does Default Risk in CouponsAffect the Valuation of Corporate Bonds? A Contingent Claims Model.*Financial Management*, vol. 22, no. 3, pp 117–131, 1993

[17] F. A. Longstaff andE. S. Schwartz, A Simple Approach to Valuing Risky Fixed and Floating Rate Debt, *Journal of Finance*, vol. 50, no. 2, pp. 789–819, 1995.

In 2001, Duffie and Lando considered a model in which the defaulting time is stable by the company´s managers to maximize the equity´s value. Investors cannot witness the assets straightly and obtain only periodic and unsatisfactory accounting reports. Default could occur unpredictably prior to the next observation. Under these conditions, the structural model develop stoareduced – form model by confusing and decreasing the information.[18]

3.5.Reduced-form models

The reduced – form models avoid some problems of structural – form models. In the reduced – form models, the timing default is influenced byan exogenous stochastic process; default event is not related to any visible characteristic of the company. Reduced – form models assume an exogenous RR that is free from the PD.

Models can be improved to contain credit rating and therefore can be used to price credit derivatives whose expenses are affected by the credit rating of the debt issue. Credit ratings also allow one to draw conclusions about the financial health of the firm without requiring information about its market value.

In 1997, Jarrow, Lando and Turnbull published first reduced-form credit model. They are studied the term structure of credit risk spreads in a model with credit ratings. Their model is the first depending rights model that clearly incorporates credit rating information into the estimation approach.[19]In 1999,also Duffie and Singleton used the credit ratings and presented a new approach to modeling the estimation of contingent rights subject to default and focus on the presentations of the term structure of interest rates for corporate bonds. Their study varies from other reduced – form models by the way they parameterize the losses in case of default.[20]

We recognize two types of models: models based on the intensity and credit migration models. Intensity model put emphasis on modelling the random time of default as a time of jump in one

[18] F. Cowell, B. Racheva andS. Trück, Recent Advances in Credit Risk Management, *Risk Assessment Decisions in Banking and Finance*, pp. 215-234, 2009.
[19] R. A. Jarrow, D. Lando, S. M. Turnbull and A. Markov, Model for the Term Structure of Credit Risk Spreads, *Review of Financial Studies*, vol. 10, no. 5, pp. 481–523, 1997
[20] D. Duffie and K. J. Singleton, Modeling the Term Structures of DefaultableBonds,*Review of Financial Studies*, vol.12, no. 2, pp.687–720, 1999

jump random process. Credit migration models transitions between credit ratings with the help of Mark's process.

3.6.Credit value-at-risk models

Through the late 1990s, certain banks developed two types of credit value-at-risk (VaR) models: nonpayment mode models and mark – to – market models. Because firm can default or survive in default mode models, credit losses occur only when the firm defaults. Mark-to-market models take more outcomes into consideration in terms of the creditworthiness of the borrower. However, losses may arise whenever the creditworthiness of the borrower changes. The most important credit value-at-risk models are Credit Metrics, KMV's Credit Portfolio Manager, Credit Risk+ and Credit Portfolio View.

A. CreditMetrics model is a theoretical framework of JP Morgan software for credit risk management called CreditManager.This modelis hybrid, using a structural as well as reduced access to measurement of VaR values of loans portfolio or securities.CreditMetrics is a method used for the calculation of credit risk of the portfolio, which shows changes in the credibility of debtor to the changes of amount of potential losses of creditor. It is structural model and falls into the category "mark – to – market" models based on the rating systems. Models of this type are based on the contention that finally the risk horizon the debtor can be defined at any of n predefined rating grades. [21]

CreditMetrics' method is created on the analysis of credit migration, i.e. the likelihood of moving from one credit quality to another, including default, within a given time horizon, which is frequently taken arbitrarily as one year. CreditMetrics approach the complete frontward distribution of the prices of any bond or loan portfolio, say one year forward, where the changes in prices are connected only to credit migration, while interest rates are expected to progress in a deterministic method. Credit – VaR of a portfolio is then derived in a parallel fashion as for market risk. It is the percentile of the circulation corresponding to the desire d confidence level.[22]

[21] E. Spuchľáková andJ. Cúg, Lost Given Default and the Credit risk, Proceedings of ICMEBIS 2014 International Conference on Management, Education, Business, and Information Science, pp. 12-15, 2014.
[22] JP Morgan, CreditMetrics-Technical Document, pp. 212, 1997.

B. The *KMV Credit Portfolio Manager* model (KMV was acquired in 2002 by Moody's) focusses on the likelihood of default of the company in one piece, rather than estimation of the debt. The KMV approach follows the logic of the structural approach. But as an end product, it comes up with the expected default frequency (EDF, created in the late 1980's) for every issuer. EDF is the likelihood of default within a specified time period. It is a purpose of the distance to default. The default likelihood is resoluted in three steps:

1. Valuation of asset value and volatility. The asset value and asset volatility of the company is valued from the market value and volatility of equity and the book value of liabilities.

2. Estimate the distance – to – default. The distance – to – default is designed from the asset value and asset volatility and the book value of liabilities.

3. Calculation of the likelihood of default. The likelihood of default is determined straight from the distance – to – default and the default rate for specified levels of distance – to – default. Historical data is used to define the consistent default likelihood.

C. *CreditRisk+*,which only focuses on default was released in 1997 by CSFP . This model adopts that the likelihood of default is small and the same in any given time period. Unlike the approaches discussed above, this model does not involve any assumptions about the causes of default, it does not associate default probability with capital structure of company, it does not estimates it with the use of historical data and assumes that default for loans can be described by a Poisson distribution. It requires only a few inputs – the default probability for each instrument: credit exposures, obligor default rates assigned to each obligor, obligor default rate volatilities and recovery rates. This model gives default rates as constant random variables and includes default rate volatility to capture the ambiguity in the level of the default rate. In this model obligors are assigned to sectors. As the amount of sectors is bigger, the concentration risk is reduced and the fat tails of the loss distribution function become lesser.[23] In 1998 McKinsey presented ***CreditPortfolioView***, witchlike CreditRisk+, measures only default risk. This model is founded on the reflection that default likelihoods are connected to economy. The deterioration of the economy increases the probability of defaults and improvement of economy reduces the

[23] Credit Suisse, CreditRisk+: A Credit Risk Management Framework, *Credit Suisse First Boston International*,pp. 70, 1997.

probability of defaults. It is a ratings – based portfolio model integrating the requirement of default and migration likelihoods on the cycle of the economic. Therefore default likelihoods and migration matrices are theme to random fluctuations.

Chapter conclusion

In this chapter, we have shown that credit risk is an inseparable part of the banking business. This risk can range from a simple delay in repayment to a total loss of the debt and interest.

The consequences of the credit risk start with a provisioning, which turns into a loss in case of an actual realization of the risk, so that the bank's results are affected, which can lead to the deterioration of its solvency and even to a systemic crisis. It is for this reason that the authorities have set up a regulation that the banks must respect.

This regulation forces the banks to control the risk they take on their counterparts. To do so, they must first assess it in order to manage it better.

The next chapter will go more indepth into one of the relatively newer methods to assess and evaluate credit risk, which is widely used by banking institutions all over the world which is the Value at Risk (VaR) approach.

Chapter 2: The Value at Risk approach to credit risk modelling

Chapter introduction

Over the past three decades, models for measuring credit risk have been developed. They are based on recent developments in financial theory or insurance theory for which the use of theory for which the use of financial market data is necessary. This is why these models are mainly applied to large listed companies.

The development of organized credit markets and the strong growth of credit derivative trading give banks the possibility to dynamically rearrange their portfolios and thus optimize the risk/return trade-off. To do this, it is necessary to build an internal credit risk management model, which is the Value at Risk.

This chapter will delve into the Value at Risk approach and how it can be used within a banking establishement to evaluate and manage financial risks and specifically credit risk and we will do so in three steps:

-Firstly we introduce the concept of VaR, its processes and methodlogies

-The second section will create a link between VaR and modern credit risk faced by banks and show how VaR can be used to manage credit risk.

-Finally we will go through the various models based on the VaR approach which aim to evaluate credit risk.

Section 1: Introduction to Value at Risk (VaR)

The advent of value-at-risk (quantifying market risk and its adoption by bank regulators are VaR) as an accepted methodology for part of the development of risk management. The application of VaR has been extended from its initial use in securities houses to commercial banks and corporates, following its introduction in October 1994 when JPMorgan launched RiskMetrics free over the Internet.

1.1.What is VaR?

VaR is an estimate of an amount of exposure cash value. It is based on probabilities, so cannot be relied on with certainty, but reflects rather a level of confidence which is selected by the user in advance. VaR measures the volatility of a company's asset prices, and so the greater the volatility, the higher the probability of loss.

Essentially VaR is a measure of the volatility of a bank trading book. It is the characteristics of volatility that traders, risk managers and others wish to become acquainted with when assessing a bank's risk exposure. The mathematics behind measuring and estimating volatility is slightly involved, and we do not go into it here. However, by making use of a volatility estimate, a trader or senior manager can gain some idea of the risk exposure of the trading book, using the VaR measure.
VaR is defined as follows:

VaR is a measure of market risk. It is the maximum loss which can occur with X% confidence over a holding period of t days.

VaR is the expected loss of a portfolio over a specified time period for a set level of probability. So, for example, if a daily VaR is stated as £100,000 to a 95% level of confidence, this means that during the day there is a only a 5% chance that the loss will be greater than £100,000. VaR measures the potential loss in market value of a portfolio using estimated volatility and correlations. It is measured within a given confidence interval, typically 95% or 99%. The tech - nique seeks to measure possible losses from a position or portfolio under 'normal' circumstances. The definition of normality is critical to the estimation of VaR and is a statistical concept; its importance varies according to the VaR calculation methodology that is being used.

1.1.1. The VaR estimation process

Broadly speaking, the calculation of a VaR estimate follows four steps:

1. Determine the time horizon over which one wishes to estimate a potential loss – this horizon is set by the user. In practice, time horizons of 1 day to 1 year have been used. For instance, bank front-office traders are often interested in calculating the amount they might lose in a 1-day period. Regulators and participants in illiquid markets may want to estimate exposures to market risk over a longer period. In any case a time horizon must be specified by the decision-maker.

2. Select the degree of certainty required, which is the confidence level that applies to the VaR estimate – knowing the largest likely loss a bank will suffer 95 times out of 100, or in fact on 1 day out of 20 (i.e., a 95% degree of confidence in this estimate, or confidence interval) may be sufficient. For regulatory requirements a 99% confidence interval may be more appropriate. Senior management and shareholders are often interested in the potential loss arising from catastrophe situations, such as a stock market crash, so for them a 99% confidence level is more appropriate.

3. Create a probability distribution of likely returns for the instrument or portfolio under consideration – several methods may be used. The easiest to understand is the distribution of recent historical returns for the asset or portfolio which often looks like the curve associated with the normal distribution.
After determining a time horizon and confidence interval for the estimate, and then collating the history of market price changes in a probability distribution, we can apply the laws of statistics to estimate VaR.

4. Calculate the VaR estimate – this is done by observing the loss amount associated with that area beneath the normal curve at the critical confidence interval value that is statistically associated with the probability chosen for the VaR estimate in Step 2.

These four steps will in theory allow us to calculate a VaR estimate ‘longhand’, although in practice mathematical models exist that will do this for us. Bearing these steps in mind, we can arrive at a practical definition of VaR not much removed from our first one:

VaR is the largest likely loss from market risk (expressed in currency units) that an asset or portfolio will suffer over a time interval and with a degree of certainty selected by the user.

We stress, of course, that this would be under 'normal', that is, unstressed conditions. There are a number of methods for calculating VaR, all logically sustainable but nevertheless reliant on some strong assumptions, and estimates prepared using the different methodologies can vary dramatically. At this point it is worthwhile reminding ourselves what VaR is not. It is not a unified method for measuring risk, as the different calculation methodologies each produce different VaR values. In addition, as it is a quantitative statistical technique, VaR only captures risks that can be quantified. Therefore, it does not measure (nor does it seek to measure) other risks that a bank or securities house will be exposed to, such as liquidity risk or operational risk. Most importantly, VaR is not 'risk management'. This term refers to the complete range of duties and disciplines that are involved in minimising and managing bank risk exposure. VaR is but one ingredient of risk management, a measurement tool for market risk exposure. So the mean and standard deviation parameters of the statistical distribution are key to the VaR estimate.

1.1.2. Methodology

A. Centralised database

To implement VaR, all of a firm's positions data must be gathered into one centralised database. Once this is complete the overall risk has to be calculated by aggregating the risks from individual instruments across the entire portfolio. The potential move in each instrument (i.e., each risk factor) has to be inferred from past daily price movements over a given observation period. For regulatory purposes this period is at least 1 year. Hence, the data on which VaR estimates are based should capture all relevant daily market moves over the previous year. The main assumption underpinning VaR – and which in turn may be seen as its major weakness – is that the distribution of future price and rate changes will follow past variations. Therefore, the potential portfolio loss calculations for VaR are worked out using distributions from historic price data in the observation period.

B. Correlation assumptions

VaR requires that the user decide which exposures are allowed to offset each other and by how much. For example, is the Japanese yen correlated to movements in the euro or the Mexican peso? Consider also the price of crude oil to movements in the price of natural gas: if there is a correlation, to what extent is the degree of correlation? VaR requires that the user determine correlations within markets as well as across markets. The mapping procedures used as part of the VaR process also have embedded correlation assumptions. For example, mapping individual stocks into the S&P 500 or fixed interest securities into the swap curve translate into the assumption that individual financial instruments move as the market overall. This is reasonable for diversified portfolios but may fall down for undiversified or illiquid portfolios.

There are three main methods for calculating VaR. As with all statistical models, they depend on certain assumptions. They are:

-Correlation method (or variance/covariance method);
-Historical simulation;
-Monte Carlo simulation.

1.1.2.1. Correlation method

This is also known as the variance–covariance, parametric or analytic method. This method assumes the returns on risk factors are normally distributed, the correlations between risk factors are constant and the delta (or price sensitivity to changes in a risk factor) of each portfolio constituent is constant. Using the correlation method, the volatility of each risk factor is extracted from the historical observation period. Historical data on investment returns are therefore required. The potential effect of each component of the portfolio on the overall portfolio value is then worked out from the component's delta (with respect to a particular risk factor) and that risk factor's volatility.

There are different methods of calculating relevant risk factor volatilities and correlations. We consider two alternatives:
1. Simple historic volatility (correlation) – this is the most straightforward method but the effects of a large one-off market move can significantly distort volatilities (correlations) over the required forecasting period. For example, if using 30-day historic volatility, a market shock will stay in the volatility figure for 30 days until it drops out of the sample range and,

correspondingly, causes a sharp drop in (historic) volatility 30 days after the event. This is because each past observation is equally weighted in the volatility calculation.

2. A more sophisticated approach is to weight past observations unequally. This is done to give more weight to recent observations so that large jumps in volatility are not caused by events that occurred some time ago. Two methods for unequal weighting are the generalised autoregressive conditional heteroscedasticity (GARCH) models and exponentially weighted moving averages. GARCH models are fine-tuned to each risk factor time series, while exponentially weighted averages can be computed with little more complication than simple historic volatility. Both methods rely on the assumption that future volatilities can be predicted from historic price movements.

1.1.2.1. Historical simulation method

The historical simulation method for calculating VaR is the simplest and avoids some of the pitfalls of the correlation method. Specifically, the three main assumptions behind correlation (normally distributed returns, constant correlations, constant deltas) are not needed in this case. For historical simulation the model calculates potential losses using actual historical returns in the risk factors and so captures the non-normal distribution of risk factor returns. This means rare events and crashes can be included in the results.
As the risk factor returns used for revaluing the portfolio are actual past movements, the correlations in the calculation are also actual past correlations. They capture the dynamic nature of correlations as well as scenarios when the usual correlation relationships break down.

1.1.2.1. Monte Carlo simulation method

The third method, Monte Carlo simulation, is more flexible than the previous two. As with historical simulation, Monte Carlo simulation allows the risk manager to use actual historical distributions for risk factor returns rather than having to assume normal returns. A large number of randomly generated simulations are run forward in time using volatility and correlation estimates chosen by the risk manager. Each simulation will be different, but in total the simulations will aggregate to the chosen statistical parameters (i.e., historical distributions and volatility and correlation estimates).
This method is more realistic than the previous two models and, therefore, is more likely to

estimate VaR more accurately. However, its implementation requires powerful computers and there is also a trade-off in that the time to perform calculations is longer.

1.2. How to calculate var

A conceptual illustration of the normal distribution being applied for VaR is given at Figure 2.

A market risk estimate can be calculated by following these steps:

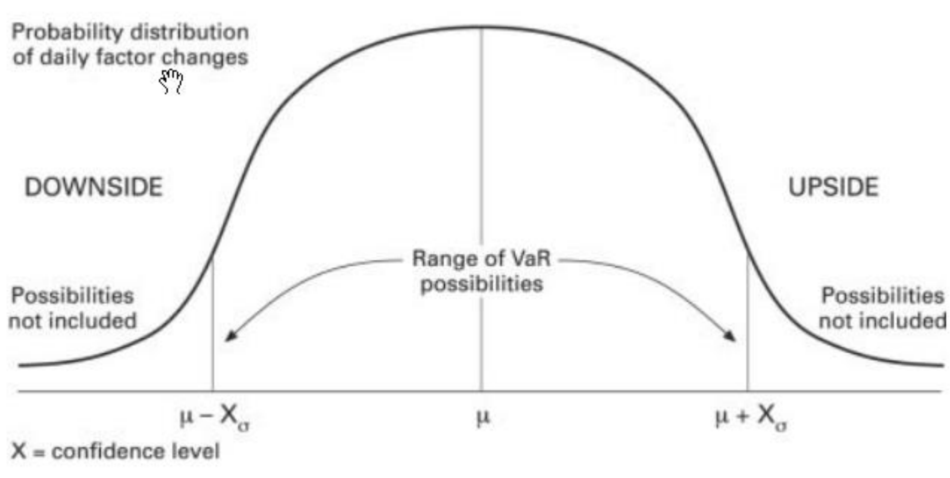
1. Value the current portfolio using today's prices, the components of which are 'market factors'. For example, the market factors that affect the value of a bond denominated in a foreign currency are the term structure of that currency's interest rate (either the zero-coupon curve or the par yield curve) and the exchange rate.

2. Revalue the portfolio using alternative prices based on changed market factors and calculate the change in the portfolio value that would result.

3. Revaluing the portfolio using a number of alternative prices gives a distribution of changes in value. Given this, a portfolio VaR can be specified in terms of confidence levels.

4. The risk manager can calculate the maximum the firm can lose over a specified time horizon at a specified probability level. In implementing VaR the main problem is finding a way to obtain a series of vectors of different market factors. We will see how the various methodologies try to resolve this issue for each of the three methods that can be used to calculate VaR.

Figure 3: VaR and the normal distribution.



1.2.1. Historical method

Values of the market factors for a particular historical period are collected and changes in these values over the time horizon are observed for use in the calculation. For instance, if a 1-day VaR is required using the past 100 trading days, each of the market factors will have a vector of observed changes that will be made up of the 99 changes in value of the market factor. A vector of alternative values is created for each of the market factors by adding the current value of the market factor to each of the values in the vector of observed changes.

The portfolio value is found using the current and alternative values for the market factors. The changes in portfolio value between the current value and the alternative values are then calculated. The final step is to sort the changes in portfolio value from the lowest value to highest value and determine the VaR based on the desired confidence interval. For a 1-day, 95% confidence level VaR using the past 100 trading days, the VaR would be the 95th most adverse change in portfolio value.

1.2.2. Simulation method

The first step is to define the parameters of the distributions for the changes in market factors, including correlations among these factors. Normal and log-normal distributions are usually used to estimate changes in market factors, while historical data are most often used to define correlations among market factors. The distributions are then used in a Monte Carlo simulation to obtain simulated changes in the market factors over the time horizon to be used in the VaR calculation.

A vector of alternative values is created for each of the market factors by adding the current value of the market factor to each of the values in the vector of simulated changes. Once this vector of alternative values of the market factors is obtained, the current and alternative values for the portfolio, the changes in portfolio value and the VaR are calculated exactly as in the historical method.

1.2.3. Variance–covariance, analytic or parametric method

This is similar to the historical method in that historical values of market factors are collected in a database. The next steps are then to :

A. Decompose financial instruments

The analytic method assumes that financial instruments can be decomposed or 'mapped' into a set of simpler instruments that are exposed to only one market factor. For example, a 2-year US bond can be mapped into a set of zero-coupon bonds representing each cash flow. Each of these zero-coupon bonds is exposed to only one market factor – a specific US zero-coupon interest rate. Similarly, a foreign currency bond can be mapped into a set of zero-coupon bonds and a cash foreign exchange amount subject to movement in the spot foreign exchange (FX) rate.

B. Specify distributions

The analytic method makes assumptions about the distributions of market factors. For example, the most widely used analytic method, JPMorgan's RiskMetrics, assumes that the underlying distributions are normal. With normal distributions all the historical information is summarised in the mean and standard deviation of the returns (market factors), so users do not need to keep all the historical data.

C. Calculate portfolio variance and VaR

If all the market factors are assumed to be normally distributed, the portfolio, which is the sum of the individual instruments, can also be assumed to be normally distributed. This means that portfolio variance can be calculated using standard statistical methods (similar to modern portfolio theory), given by:

$$\sigma_{\rho} = \sqrt{\alpha_j^2\sigma_j^2 + \alpha_k^2\sigma_k^2 + 2\alpha_j\alpha_k\rho_{jk}\sigma_j\sigma_k}$$

Where α_j= Home currency present value of the position in market factor j;

σ_j^2= Variance of market factor j;

ρ_{jk}= Correlation coefficient between market factors j and k.

The portfolio VaR is then a selected number of portfolio standard deviations; for example, 1.645 standard deviations will isolate 5% of the area of the distribution in the lower tail of the normal curve, providing 95% confidence in the estimate.

Consider an example where, using historical data, the portfolio variance for a package of US bond is \$348.57. The standard deviation of the portfolio would be $\sqrt{348.57}$, which is \$18.67. A 95% 1-day VaR would be 1.645 × \$18.67, which is \$30.71.

Of course, a bank's trading book will contain many hundreds of different assets, and the method employed above, useful for a twoasset portfolio, will become unwieldy. Therefore, matrices are used to calculate the VaR of a portfolio where many correlation coefficients are used.

Section 2 : Modern credit risk and VaR

Credit risk is a definition of the outcome of banking. However, in increasingly competitive markets, banks and securities houses take on more credit risk. The following are instances:

-Credit spreads tightened in the late 1990s and the early part of 2000 to the point where blue chip companies – such as BT or Shell – benefitted from syndicated loan rates for as little as 10–12 basis points over the London Interbank Offered Rate (LIBOR); banks are turning to lower rated firms to maintain margin;

-Growth in complex financial instruments that are more challenging to manage for credit risk than traditional instruments, such as collateralised debt obligations (CDOs);

-Investors are finding fewer opportunities in interest rate and currency markets and moving towards yield enhancement through extending and trading credit; for example, in the eurozone participating government bond markets become credit markets and are in some cases very low-rated;

-High yield (junk) and emerging market sectors have been expanding rapidly.

The growth in credit exposures and rise of complex instruments have led to a need for more accurate risk measurement techniques. We discuss the application of the VaR methodology for credit risk exposure.

2.1.Types of credit risk

There are two main types of credit risk:

• Credit spread risk

• Credit default risk.

We consider each now.

2.1.1. Credit spread risk:

Credit spread is the excess premium required by the market for taking on a certain assumed credit exposure. Credit spread risk is the risk of financial loss resulting from changes in the level of credit spreads used in the marking-to-market of a product. It is exhibited by a portfolio for which the credit spread is traded and marked. Changes in observed credit spreads affect the value of the portfolio.

2.1.2. Credit default risk:

This is the risk that an issuer of debt (obligor) is unable to meet its financial obligations. Where an obligor defaults, a firm generally incurs a loss equal to the amount owed by the obligor less any recovery amount which the firm gets back as a result of foreclosure, liquidation or restructuring of the defaulted obligor. All portfolios of risky exposures exhibit credit default risk.

2.2. Credit ratings

The risks associated with holding a fixed interest debt instrument are closely connected with the ability of the issuer to maintain regular coupon payments as well as redeem the debt on maturity. Essentially, credit risk is the main risk of holding a bond. Only the highest quality government debt, and a small amount of supra-national and corporate debt, may be considered to be entirely free of credit risk. Therefore, at any time, the yield on a bond reflects investors' views on the ability of the issuer to meet its liabilities as set out in the bond's terms and conditions. A delay in paying a cash liability as it becomes due is known as technical default and is a cause for extreme concern for investors; failure to pay will result in the matter being placed in the hands of a court as investors seek to recover their funds.

A credit rating is a formal opinion given by a rating agency of the credit risk for investors in a particular issue of debt securities. Ratings are given to public issues of debt securities by any type of entity, including governments, banks and corporates. They are also given to short-term debt, such as commercial paper, as well as bonds and medium-term notes.

Credit ratings are provided by specialist agencies. The major credit rating agencies are Standard & Poor's, Fitch, and Moody's, based in the United States. There are other agencies both in the US and other countries. On receipt of a formal request, the credit rating agencies will carry out a rating exercise on a specific issue of debt capital. The request for a rating comes from the organisation planning the issue of bonds. Although ratings are provided for the benefit of investors, the issuer must bear the cost. However, it is in the issuer's interest to request a rating as it raises the profile of the bonds, and investors may refuse to buy paper that is not accompanied by a recognised rating.

Although the rating exercise involves a credit analysis of the issuer, the rating is applied to a specific debt issue. This means that in theory the credit rating is applied not to an organisation itself, but to the specific debt securities that the organisation has issued or is planning to issue. In practice, it is common for the market to refer to the creditworthiness of organisations themselves in terms of the rating of their debt. A highly rated company, such as ExxonMobil, is therefore referred to as a 'triple-A rated' company, although it is the company's debt issues that are rated as triple-A.

2.3.Ratings changes over time (*Ratings transition matrix)*

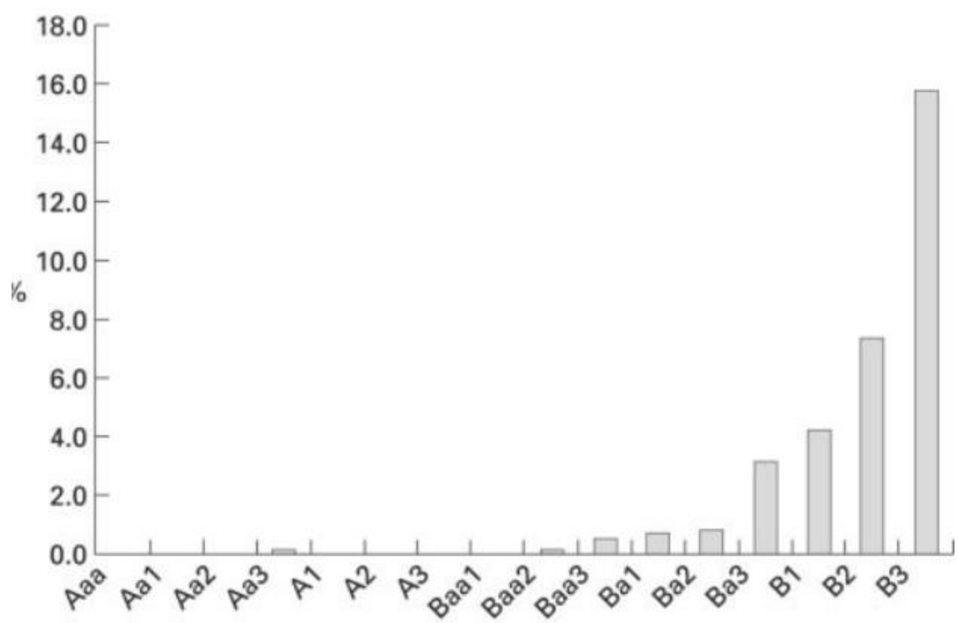
We have noted that the rating agencies constantly review the credit quality of firms they have rated. As might be expected, the credit rating of many companies will fluctuate over time as they experience changes in their corporate well-being. As a guide to the change in credit rating that might be expected over a 1-year period, Moody's and S&P publish historical transition matrices, which provide the average rating transition probabilities for each class of rating.
An example is shown at Table 3 , which is Moody's 1-year ratings transition matrix for 2002. These results are obtained from a sample of a large number of firms over many years. In Table 3, the first column shows the initial rating and the first row the final rating. For instance, the probability of an A-rated company being downgraded to Baa in 1 year is 4.63%. The probability of the A-rated company defaulting in this year is 0.00%.

Table 3 : Moody's 1-year rating transition matrix (%)

	Aaa	*Aa*	*A*	*Baa*	*Ba*	*B*	*Caa*	*Default*
Aaa	93.40	5.94	0.64	0.00	0.02	0.00	0.00	0.00
Aaa	1.61	90.55	7.46	0.26	0.09	0.01	0.00	0.02
Aaa	0.07	2.28	92.44	4.63	0.45	0.12	0.01	0.00
Baa	0.05	0.26	5.51	88.48	4.76	0.71	0.08	0.15
Baa	0.02	0.05	0.42	5.16	86.91	5.91	0.24	1.29
Baa	0.00	0.04	0.13	0.54	6.35	84.22	1.91	6.81
Caa	0.00	0.00	0.00	0.62	2.05	4.08	69.20	24.06

There are some inconsistencies in the ratings transition table and this is explained by Moody's as resulting from scarcity of data for some ratings categories. For instance, an Aa-rated company has a 0.02% probability of being in default at year-end, which is higher than the supposedly lower rated A-rated company. So at all times such results must be treated with care. The clearest conclusion from this table is that the most likely outcome at year-end is that the company rating remains the same. It may be that a 1-year time horizon provides little real value; hence, the rating agencies also publish transition matrices for longer periods, such as 5 and 10 years.

Figure 4: One-year default rates 1985–2000.



We might expect an increased level of default as we move lower down the credit ratings scale. This is borne out in Figure 3 , which is a reproduction of data published by Moody's. It shows 1-year default rates by credit rating category, for the period 1985–2000. We see that the average 1-year default rate rises from 0 for the highest rated Aaa to 15.7% for the B3 rating category. As we have just suggested though, some investors attach little value to 1-year results.

Figure 5: Both 5-year and 10-year average cumulative default

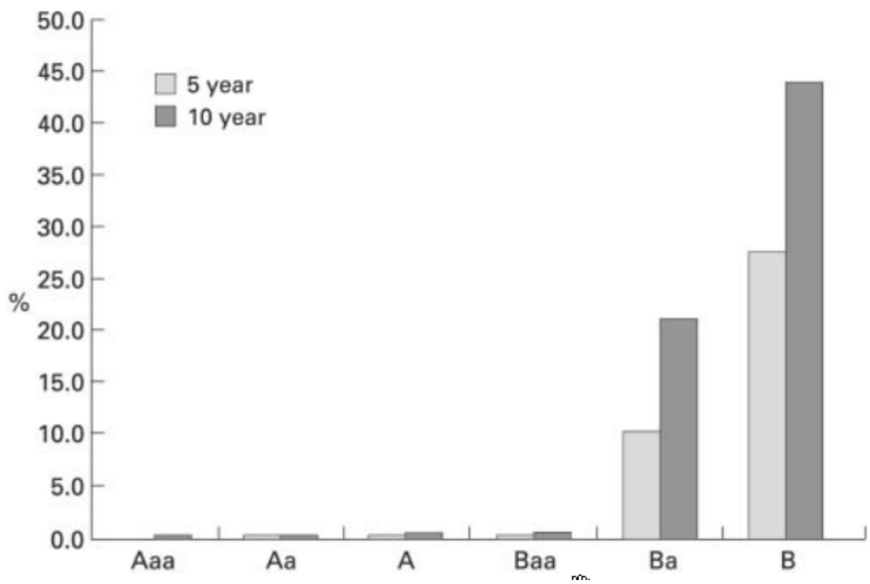


Figure 4 shows average cumulative default rates for 5-year and 10-year time horizons, for the same period covered in Figure 3. In fact, this repeats the results shown in Table 3, with higher default rates associated with lower credit ratings.

2.4.Corporate recovery rates

When a corporate obligor experiences bankruptcy or enters into liquidation or administration, it will default on its loans. However, this does not mean that all the firm's creditors will lose everything. At the end of the administration process, the firm's creditors typically will receive back a portion of their outstanding loans, a recovery amount. The percentage of the original loan that is received back is known as the recovery rate, which is defined as the percentage of par value that is returned to the creditor.

Table 4: Recovery rates according to loan seniority (%)

Seniority	*Mean*	*Standard deviation*
Senior secured bank loans	60.70	26.31
Senior secured	55.83	25.41
Senior unsecured	52.13	25.12
Senior subordinated	39.45	24.79
Subordinated	33.81	21.25
Junior subordinated	18.51	11.26
Preference shares	8.26	10.45

The seniority of a loan strongly influences the level of the recovery rate. Table 4 shows recovery rates for varying levels of loan seniority in 2002, as published by Moody's. The standard deviation for each recovery rate reported is high, which illustrates dispersion around the mean and reflects widely varying recovery rates even within the same level of seniority. It is clear that the more senior a loan or a bond is, the higher recovery it will enjoy in the event of default.

2.5.Modeling credit risk using VaR

The main credit risk VaR methodologies take a portfolio approach to credit risk analysis. This means that:

-The credit risks to each obligor across the portfolio are restated on an equivalent basis and aggregated in order to be treated consistently, regardless of the underlying asset class;

-Correlations of credit quality moves across obligors are taken into account.

This allows portfolio effects – the benefits of diversification and risks of concentration – to be quantified. The portfolio risk of an exposure is determined by four factors:

• Size of the exposure;

• Maturity of the exposure;

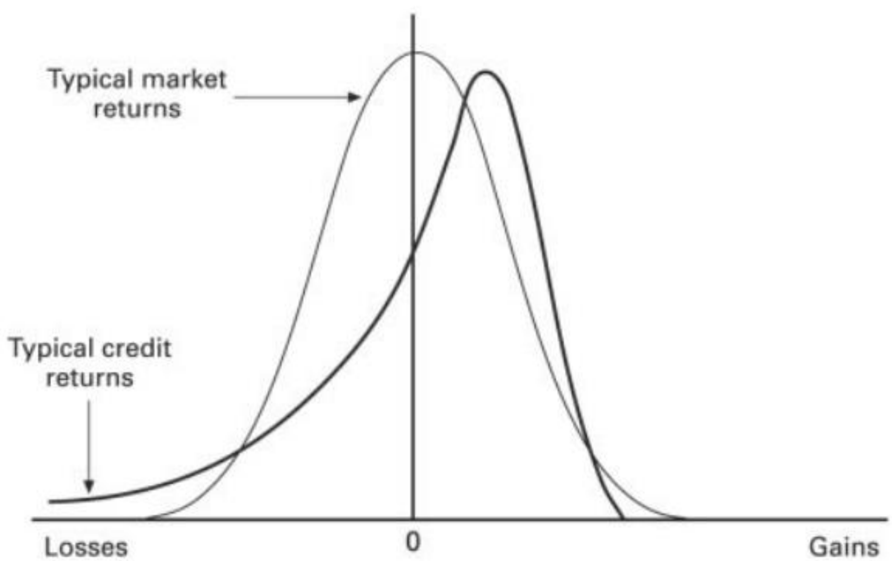
• Probability of default of the obligor;

• Systematic or concentration risk of the obligor.

Credit VaR – like market risk VaR – considers (credit) risk in a markto-market framework. It arises from changes in value due to credit events; that is, changes in obligor credit quality including defaults, upgrades and downgrades.

Nevertheless, credit risk is different in nature from market risk. Typically, market return distributions are assumed to be relatively symmetrical and approximated by normal distributions. In credit portfolios, value changes will be relatively small upon minor upgrades/downgrades, but can be substantial upon default. This remote probability of large losses produces skewed distributions with heavy downside tails that differ from the more normally distributed returns assumed for market VaR models. This is shown in Figure 5

Figure 6: Comparison of distribution of market returns and credit



This difference in risk profiles does not stop City quantitative analysts from assessing risk on a comparable basis. Analytical method market VaR models consider a time horizon and estimate VaR across a distribution of estimated market outcomes. Credit VaR models similarly look to a horizon and construct a distribution of value given different estimated credit outcomes.

When modelling credit risk the two main measures of risk are:

-Distribution of loss – obtaining distributions of loss that may arise from the current portfolio. This considers the question of what the expected loss is for a given confidence level;

-Identifying extreme or catastrophic outcomes – this is addressed through the use of scenario analysis and concentration limits.

To simplify modelling, no assumptions are made about the causes of default. Mathematical techniques used in the insurance industry are used to model the event of an obligor default.

2.5.1. Time horizon

The choice of time horizon will not be shorter than the time frame over which risk-mitigating actions can be taken. Most analysts suggest two alternatives:
-A constant time horizon such as 1 year;
-A hold-to-maturity time horizon.

2.5.2. Data inputs

Modelling credit risk requires certain data inputs; generally these are the following:
• Credit exposures;
• Obligor default rates;
• Obligor default rate volatilities;
• Recovery rates.

These data requirements present some difficulties. There is a lack of comprehensive default and correlation data, and assumptions need to be made at certain times.

Section 3: The most significant methods of measuring credit VaR

3.1.Creditmetrics

CreditMetrics was JPMorgan's portfolio model for analysing credit risk and was the first such credit VaR model, providing an estimate of VaR due to credit events caused by upgrades, downgrades and default. A software package known as CreditManager was made available that allows users to implement the CreditMetrics methodology.

3.1.1. Methodology

There are two main frameworks in use for quantifying credit risk. One approach considers only two states: default and non-default. This model constructs a binomial tree of default vs no-default outcomes until maturity (see Figure 6).

The other approach, sometimes called the risk-adjusted return on capital (RAROC) approach holds that risk is the observed volatility of corporate bond values within each credit rating category, maturity band and industry grouping. The idea is to track a benchmark corporate bond (or index) which has observable pricing. The resulting estimate of volatility of value is then used to proxy the volatility of the exposure (or portfolio) under analysis.

CreditMetrics sits between these two approaches. The model estimates portfolio VaR at the risk horizon due to credit events that include upgrades and downgrades, rather than just defaults. Thus, it adopts a mark-to-market framework. As shown in Figure 7 bonds within each credit rating category have volatility of value due to day-to-day credit spread fluctuations. CreditMetrics assumes that all credit migrations have been realised, weighting each by a migration likelihood.

Figure 7: A binomial model of credit risk.

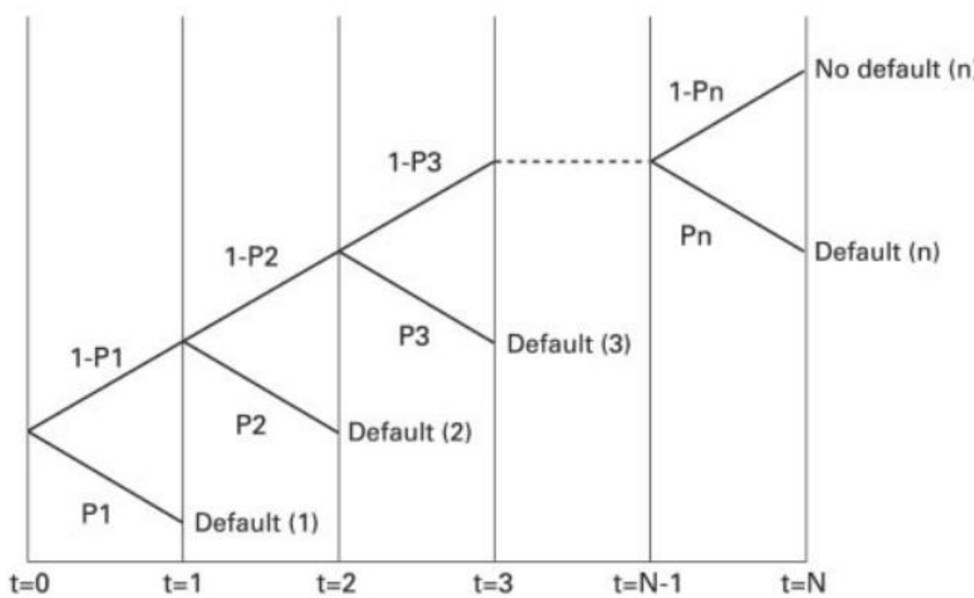
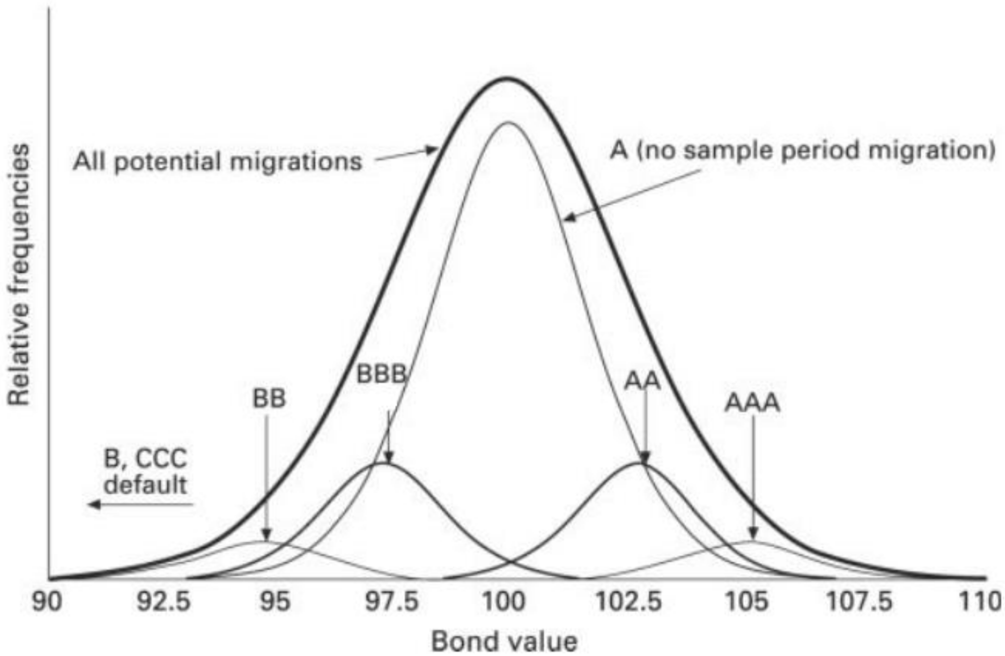


Figure 8: Ratings migration distribution.



3.1.2. Time horizon

CreditMetrics adopts a 1-year risk horizon mainly because much academic and credit agency data are stated on an annual basis. This is a convenient convention similar to the use of annualised interest rates in the money markets. The risk horizon is adequate as long as it is not shorter than the time required to perform risk-mitigating actions.

-The steps involved in CreditMetrics methodology are shown in Figure 8, described by RiskMetrics as its analytical ‘roadmap’. The elements in each step are:

- **Exposures:**
  - ►User portfolio;
  - ►Market volatilities;
  - ►Exposure distributions.
- **VaR due to credit events:**
  - ►Credit rating;
  - ►Credit spreads;

►Rating change likelihood;

►Recovery rate in default;

►Present value bond revaluation;

►Standard deviation of value due to credit quality changes.

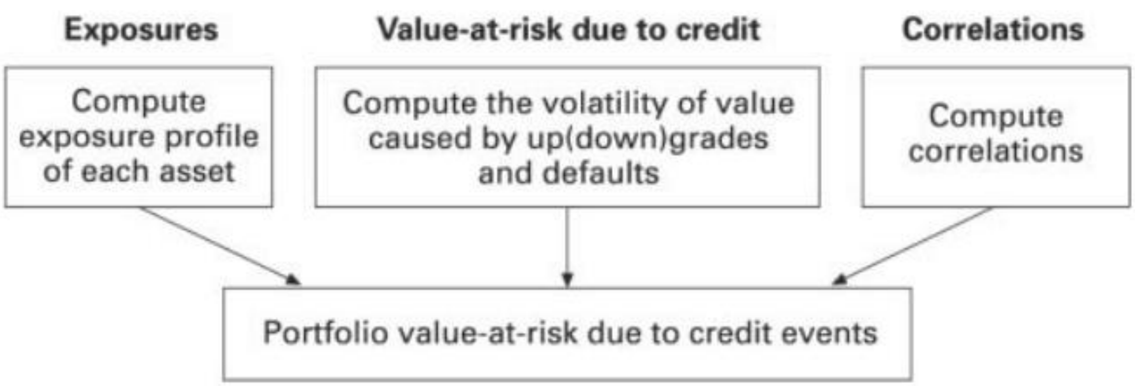
• **Correlations:**

-Ratings series;

-Models (e.g., correlations);

-Joint credit rating changes.

Figure 9: Roadmap of the analytics of CreditMetrics.



3.1.3. Calculating the credit VaR

CreditMetrics' methodology assesses individual and portfolio VaR due to credit in three steps:

Step 1: It establishes the exposure profile of each obligor in a portfolio.
Step 2: It computes the volatility in value of each instrument caused by possible upgrade, downgrade and default.
Step 3: Taking into account correlations between each of these events it combines the volatility of the individual instruments to give an aggregate portfolio risk.

Step 1 : Exposure profiles

CreditMetrics incorporates the exposure of instruments such as bonds (fixed or floating rate) as well as other loan commitments and market-driven instruments, such as swaps. Exposure is stated on an equivalent basis for all products. The products covered include:

-receivables (or trade credit);
-bonds and loans;
-loan commitments;
-letters of credit;
-market-driven instruments.

Step 2 : Volatility of each exposure from upgrades, downgrades and defaults

The levels of likelihood are attributed to each possible credit event of upgrade, downgrade and default. The probability that an obligor will change over a given time horizon to another rating is calculated. Each change (migration) results in an estimated change in value (derived from credit spread data and, in default, recovery rates). Each value outcome is weighted by its likelihood to create a distribution of value across each credit state, from which each asset's expected value and the volatility (standard deviation) of value are calculated.

There are three stages to calculating the volatility of value in a credit exposure:

-The senior unsecured credit rating of the issuer determines the chance of either defaulting or migrating to any other possible credit quality state in the risk horizon;

-Revaluation at the risk horizon can be by either (i) the seniority of the exposure, which determines its recovery rate in case of default, or (ii) the forward zero-coupon curve (spot curve) for each credit rating category which determines the revaluation upon upgrade or downgrade;

-The probabilities from the two steps above are combined to calculate the volatility of value due to credit quality changes.

Step 3 Correlations

Individual value distributions for each exposure are combined to give a portfolio result. To calculate the portfolio value from the volatility of individual asset values requires estimates of the correlation between credit quality changes. CreditMetrics itself allows for different approaches to estimating correlations including a simple constant correlation. This is because of the frequent difficulty in obtaining directly observed credit quality correlations from historical data.

3.1.4. CreditManager

CreditManager was the software implementation of CreditMetrics as originally developed by JPMorgan. It is a PC-based application that measures and analyses credit risk in a portfolio context. It measures the VaR exposure due to credit events across a portfolio, and also quantifies concentration risks and the benefits of diversification by incorporating correlations (following the methodology utilised by CreditMetrics). The CreditManager application provides a framework for portfolio credit risk management that can be implemented 'off-the-shelf' by virtually any institution. It uses the following:

- Obligor credit quality database – details of obligor credit ratings, transition and default probabilities, industries and countries;

- Portfolio exposure database – containing exposure details for the following asset types: loans, bonds, letters of credit, total return swaps, CDS, interest rate and currency swaps and other market instruments;

- Frequently updated market data – including yield curves, spreads, transition and default probabilities;

- Flexible risk analyses with user-defined parameters – supporting VaR analysis, marginal risk, risk concentrations, event risk and correlation analysis;

- Stress-testing scenarios – applying user-defined movements to correlations, spreads, recovery rates, transition and default probabilities;

- Customised reports and charts.

CreditManager data sources include Dow Jones, Moody's, Reuters, and Standard & Poor's. By using the software package, risk managers can analyse and manage credit portfolios based on virtually any variable, from the simplest end of the spectrum – single position or obligor – to more complex groupings containing a range of industry and country obligors and credit ratings.

Generally, this quantitative measure is employed as part of an overall risk management framework that retains traditional, qualitative methods.

CreditMetrics can be a useful tool for risk managers seeking to apply VaR methodology to credit risk. The model enables risk managers to apply portfolio theory and VaR methodology to credit risk. It has several applications including prioritising and evaluating investment decisions and, perhaps most important, setting risk-based exposure limits. Ultimately, the model's sponsors claim its use can aid maximising shareholder value based on risk-based capital allocation. This should then result in increased liquidity in credit markets, the use of a marking-to-market approach to credit positions and closer interweaving of regulatory and economic capital.

3.2.CredirRisk+

Shortly after **J.** P. Morgan published the portfolio model CreditMetrics™, Credit Suisse Financial Products (CSFP) introduced its own portfolio model CreditRisk+™ in October 1997. The model was created by Tom Wilde of CSFP and is still unique among existing portfolio models with respect to the mathematics involved. CreditRisk+ applies techniques from actuarial mathematics in an enhanced way to calculate the probabilities for portfolio loss levels (i.e. the portfolio loss distribution).

In contrast to JP Morgan, CSFP decided not to market its credit risk model but to publish adequate information on the basics of CreditRisk+. Those banks used to buying complete solutions for their problems avoided the CSFP model. However, for other banks CreditRisk+ became a popular choice, used in business units such as Treasury, Credit Treasury, Controlling and Portfolio Management. It was not surprising therefore that CreditRisk+ - along with CreditMetrics - played a significant role in the development of the New Basel Capital Accord.

One of the main reasons for the success of CreditRisk+ is that it is the only credit risk model that focuses on the event of default, which is the event of most interest in all credit risk analysis. Moreover, it can easily be adapted to different kinds of credit business. This makes it particularly popular amongst practitioners who need to work with a credit risk model and its developments fitted to their needs.

Finally, one more price component is the assumption that recovery rates and defaults are independent of one another. This is a common assumption made by several other credit risk models. A cautious approach, to cope with this problem and to acknowledge the fact of negative correlation, is the use of conservatively estimated recovery rates.

3.2.1. Foundations of the CreditRisk+ model

Basically, CreditRisk+ is a default mode model that mimics acturial mathematics in order to describe credit risk in a portfolio. There are only a few fundamental ideas for the model, which can be summarized as follows:

• No model for default event: The reason for a default of an obligor is not the subject of the model. Instead the default is described as a purely random event, characterized by a probability of default.

• Stochastic probability of default: The probability of default of an obligor is not seen as a constant, but a randomly varying quantity, driven by one or more (systematic) risk factors, the distribution of which is usually assumed to be a gamma distribution.

• Linear dependence on risk factors: A linear relationship between the systematic risk factors and the probabilities of default is assumed.

• Conditional independence: Given the risk factors the defaults of obligors are independent.

• Only implicit correlations via risk drivers: Correlations between obligors are not explicit, but arise only implicitly due to common risk factors which drive the probability of defaults.

• Discretization of losses: In order to aggregate losses in a portfolio in a comfortable way, they are represented as multiples of a common loss unit.

• Use of probability-generating functions: The distribution of losses is derived from probability-generating functions, which can be used if the losses take discrete values.

• Approximation of loss distribution: In order to obtain the loss distribution for the portfolio with acceptable effort, an approximation for the probability-generating functions is used, which usually corresponds to a Poisson approximation for the loss of an obligor.

These ideas result in the following characteristic features of CreditRisk+:

• The resulting portfolio loss distribution is described by a sum of independent compound negative binomial random variables.

• The distribution and its characteristic quantities can be calculated analytically in a fast and comfortable way; no simulations are necessary.

3.2.2. Reasons for Adoption

In Creditllisk+ the development of a loan is understood as a Bernoulli random variable: either the obligor pays the amount due or the loan defaults. No profits or losses from rating migrations have to be considered. In contrast, CreditMetrics tries to model a mark-to-market approach of liquid loans, in which each cash flow is discounted at a rate that is appropriate for its overall rating. The uncertainty of the future rating presents the source of randomness. It is not simply a question of two possibilities (obligor pays or defaults) being of interest, as there are as many possibilities as there are rating classes. Experts in the lending business quickly realized that Creditllisk+ is more intuitive than CreditMetrics and better suited to practical needs. There is no requirement to provide the complete cash flow vector for each loan and no requirement to update spread curves for each rating class on a regular basis.

One final remark with respect to CreditMetrics seems appropriate: the mark-to-market approach of CreditMetrics is in most cases merely a markto-model approach. But the model does not pay you cash if the rating of the loan has improved. Hence, CreditMetrics sometimes measures (pseudo-markto-market) profits that cannot be realized.

Since Creditllisk+ is an analytic-based portfolio approach it allows the rapid and unambigous calculation of the loss distribution. The speed of the calculation is helpful when comparative statistics ("what if' analyses) are performed, e.g. for analysing a new deal with a significant influence on the loss distribution or for pricing asset-backed securities (ABS) in a wider sense (ABS, mortgage-backed-securities (MBS), collateralized debt obligations (CDO), etc.) including different scenarios for the parameters.

Since practitioners tend to base decisions on their calculations, the unambiguity of the distribution is important - especially as far as the tail of the loss distribution is concerned. However, simulation-based portfolio approaches usually fail to give a single answer because their results depend on the number of simulation runs, type of random numbers, etc.

CreditRisk+ shows even greater flexibility. In accounting for stochastic probabilities of default with different expected values and rich structures of default correlation among the obligors and different levels of (net) exposures, CreditRisk+ analytically derives an algorithm for the calculation of the loss distribution. It thus avoids the need to manage simulations.

3.2.3. Limits

Disregarding its numerous advantages, there is a price to pay for the analytical nature of CreditRisk+: for example the Poisson approximation in CreditRisk+ requires the expected default probabilities to be small, typically a single digit percentage figure. This approximation leads to two astonishing phenomena: firstly, there is normally some probability of the calculated losses being larger than the sum of the net exposures, i.e. you can lose more money than you have lent! Secondly, the risk contributions (as calculated in the original version) may turn out higher than the net exposure itself. However, even if the model is operated with moderate levels of expected default probabilities, high levels may return through the back door by setting high levels of standard deviations for the default probabilities. Fortunately, the probability of losses larger than the sum of the net exposures can be quantified. This usually reveals that the price is lower than expected.

A further price component is the limited range of default correlation that can be produced by CreditRisk+. Due to the mathematical approach chosen (the intensity approach), the original CreditRisk+ produces only positive and usually moderate levels of default correlation among two obligors sharing a common risk driver. In a particular industry, default correlation may theoretically be negative because one company can take capacity away from a defaulting competitor and thus decrease its default probability. However, economy-wide systematic risk factors should outweigh this negative dependence to a large extent. Summing up default correlation should be positive. The only price paid is the limited range that Creditllisk+- in its original version - can produce. There are ways to deal with this. One example for achieving the extreme case of a perfect default correlation is an artificial merger of two clients into one net exposure figure.

We will first explain the basic model setting and then proceed to the CreditRisk+ modelling process

3.2.4. Basic Model Setting

We consider the portfolio of N obligors. Obligor n constitutes a loss exposure E_n and has a probability of default PD_n over the time period $[0, T]$. The *loss exposure* is given by its exposure at default EAD_n times its expected percentage loss given default ELGD_n,

i.e. $E_n = \text{EAD}_n \cdot \text{ELGD}_n$.

The state of obligor n at the time horizon T can be represented as a Bernoulli random variable D_n where

$$D_n = \begin{cases} 1 \text{ if obligor n defaults at time T }, \\ 0 \text{ otherwise.} \end{cases}$$

Hence the default probability is $P(D_n = 1) = \text{PD}_n$ while the survival probability is given by $P(D_n = 0) = 1 - \text{PD}_n$. In the full CreditRisk+ model, the Bernoulli parameter PD_n is taken stochastic as well and the default indicator variables D_n are conditionally independent, i.e.

$$(D_n \mid \text{PD}_1, \dots, \text{PD}_N)_n \text{ independent } \sim \text{Bern}(1; \text{PD}_n)$$

Definition

The *probability generating function* (PGF) of a non-negative integer-valued random variable X is defined as

$$G_X(z) = \mathbb{E}[z^X] = \sum_{i=0}^{\infty} z^i \cdot \mathbb{P}[X = i]$$

From this definition it immediately follows that

$$\mathbb{P}[X = i] = \frac{1}{i!} G_X^{(i)}(0), i \in \mathbb{N}_0$$

where $G_X^{(i)}(0)$ denotes the i-th derivative of the PGF $G_X(z)$ evaluated at $z = 0$. Thus the distribution of a random variable can easily be computed as soon as one knows the PGF. The CreditRisk+ model makes use of exactly this property as well. Before returning to the derivation of the CreditRisk+ model, we will briefly state some properties of the PGF which will be extensively used in the following.

Proposition Let X, Y be two random variables.

1. Let X, Y be independent. Then the PGF of X + Y is simply the product of the PGF of X and the PGF of Y, i.e.

$$G_{X+Y}(z) = G_X(z) \cdot G_Y(z)$$

4. Let GX|Y (z) be the PGF of X conditional on the random variable Y and denote the distribution function of Y by F. Then

$$G_X(z) = \int G_{X|Y=y}(z) F(dy)$$

Proof.

1. Since X, Y are independent, it follows that also z^X, z^Y are independent. Thus we have $E[z^{X+Y}] = E[z^X] \cdot E[z^Y]$ which proves the first statement.

2. The second statement follows from

$$G_X(z) = \mathbb{E}[z^X] = \int \mathbb{E}[z^X \mid Y = y] F(dy) = \int G_{X|Y=y}(z) F(dy)$$

Note that the probability generating function (PGF) of D_n can be computed to

$$G_{D_n}(z) = \sum_{x=0}^{\infty} \mathbb{P}(D_n = x) \cdot z^x = (1 - \mathrm{PD}_n) + \mathrm{PD}_n \cdot z \qquad (1)$$

The loss of obligor n is given by the random variable $Ln = D_n \cdot E_n$. Hence we can compute the probability distribution of Ln as $P(L_n = E_n) = PD_n$ and $P(L_n = 0) = 1 - PD_n$. The total portfolio loss L is given by

$$L = \sum_{n=1}^{N} L_n = \sum_{n=1}^{N} D_n \cdot E_n$$

In the CreditRisk+ model the expected loss given defaults $ELGD_n$ are usually modeled as constant fractions of the loan size. To limit the number of possible values for L the loss exposure amounts are expressed as integer multiples of a fixed base unit of loss. Therefore one can, for example, choose the smallest exposure as the normalization factor and express all other exposures in multiples of this smallest exposure. Denote for example the base unit of loss by E, then the normalized exposure of obligor n is $v_n = EAD_n/E \cdot ELGD_n = E_n/E$. In the following we denote the normalized loss of obligor n by $\lambda_n = D_n \cdot v_n$. Hence, λ_n is a random variable taking value vn with probability PD_n and value 0 with probability $1 - \mathrm{PD}_n$. The total normalized portfolio loss is $\lambda = \sum_{n=1}^{N} \lambda_n$.

In order to be able to compute the VaR for the portfolio (or equivalently any other risk measure for the portfolio) we need to derive the probability distribution of the portfolio loss L. Instead of determining the probability distribution of L, however, we can also derive the distribution of λ. For intuition, we will start with an example of a simplified version of the CreditRisk+ model with non-random default probabilities.

Example (Non-Random Default Probabilities) In the simplified case of non-random default probabilities, the PGF of the portfolio loss can easily be computed. Here we assume that individual default probabilities are known with certainty, and that default events are independent among obligors.

The PGF of D_n is given by equation from which we can easily derive the PGF of λ_n by the relation $\lambda_n = D_n \cdot v_n$. Since obligors are independent and since λ is the sum of λ_n over n, the PGF of λ is simply

$$G_\lambda(z) = \prod_{n=1}^{N} G_{\lambda_n}(z) = \prod_{n=1}^{N} [(1 - \mathrm{PD}_n) + \mathrm{PD}_n \cdot z^{v_n}]$$

3.2.5. The modelling process

CreditRisk+ uses a two-stage modelling process as illustrated in Figure 9

CreditRisk+ considers the distribution of the number of default events in a time period, such as 1 year, within a portfolio of obligors having a range of different annual probabilities of default. The annual probability of default of each obligor can be determined

by its credit rating and then mapping between default rates and credit ratings. A default rate can then be assigned to each obligor (an example of what this would look like is shown in Table 5).

Default rate volatilities can be observed from historic volatilities.

Figure 10: CreditRisk+ modelling methodology

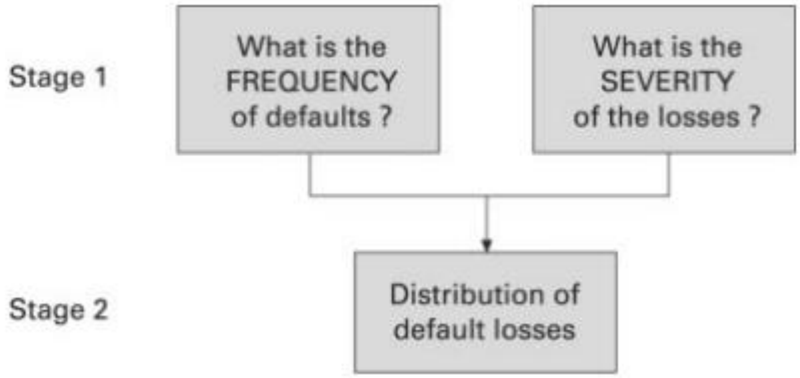


Table 5 : One-year default rates (%)

Credit rating	*One-year default rate*
Aaa	0.00
Aa	0.03
A	0.01
Baa	0.12
Ba	1.36
B	7.27

Source: CSFB

3.2.5.1. Correlation and background factors

Default correlation impacts the variability of default losses from a portfolio of credit exposures. CreditRisk+ incorporates the effects of default correlations by using default rate volatilities and sector analysis.

Unsurprisingly enough, it is not possible to forecast the exact occurrence of any one default or the total number of defaults. Often there are background factors that may cause the incidence

of default events to be correlated, even though there is no causal link between them. For example, an economy in recession may give rise to an unusually large number of defaults in one particular month, which would increase the default rates above their average level.

CreditRisk+ models the effect of background factors by using default rate volatilities rather than by using default correlations as a direct input. Both distributions give rise to loss distributions with fat tails.

3.2.5.2. Concentration

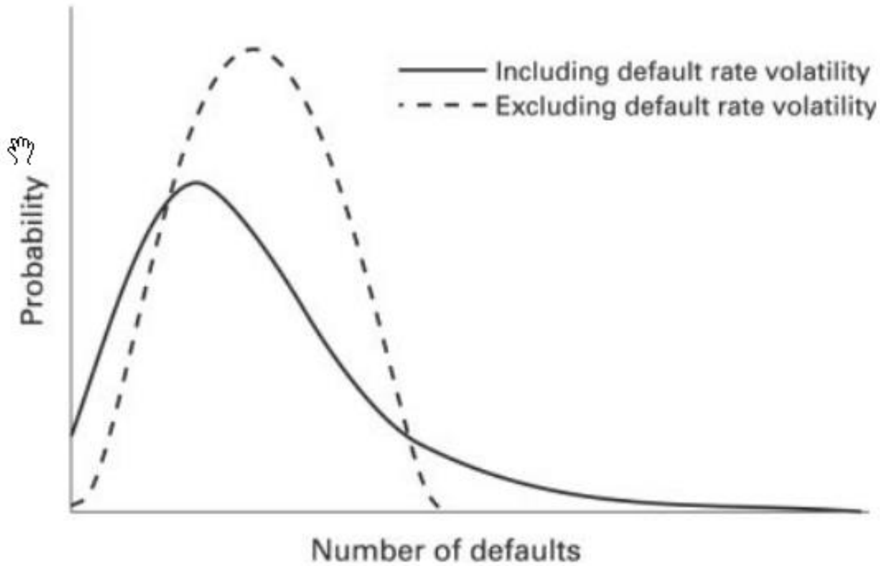
As noted above there are background factors that affect the level of default rates. For this reason it is useful to capture the effect of concentration in particular countries or sectors. CreditRisk+ uses sector analysis to allow for concentration. Exposures are broken down into an obligor-specific element independent of other exposures, as well as non-specific elements that are sensitive to particular factors, such as countries or sectors.

3.2.5.3. Distribution of the number of default events

CreditRisk+ models the underlying default rates by specifying a default rate and a default rate volatility. This aims to take account of the variation in default rates. The effect of using volatility is illustrated in Figure 10, which shows the distribution of default rates generated by the model when rate volatility is varied. The distribution becomes skewed to the right when volatility is increased.

This is an important result and demonstrates the increased risk represented by an extreme number of default events. By varying the volatility in this way, CreditRisk+ is attempting to model for real-world shock much in the same way that market risk VaR models aim to allow for the fact that market returns do not follow exact normal distributions, as shown by the incidence of market crashes.

Figure 11: CreditRisk+ distribution of default events



3.2.5.4. Application software

CreditRisk+ is run on Microsoft Excel as a spreadsheet calculator. The user inputs portfolio statistics into a blank template and the model will calculate his credit exposure. Obligor exposure can be analysed on the basis of all exposures being part of the same sector; alternatively, up to eight different sectors (government, countries, industry and so on) can be analysed. The spreadsheet template allows the user to include up to 4,000 obligors in the static data. An example portfolio of 25 obligors and default rates and default rate volatilities (assigned via a sample of credit ratings) is included with the spreadsheet.

The user's static data for the portfolio will therefore include details of each obligor, the size of the exposure, the sector for that obligor (if not all in a single sector) and default rates. An example of static data is given in Tables 6 and 7.

An example credit loss distribution calculated by the model is shown in Figure 11, which shows the results for a portfolio at the simplest level of assumption; all obligors are assigned to a single sector. The full loss distribution over a 1-year time horizon is calculated together with percentiles of the loss distribution (not shown here), which assess the relative risk for different levels of loss. The model can calculate distributions for a portfolio with obligors grouped across different sectors, as well as the distribution for a portfolio analysed over a 'hold to maturity' time horizon.

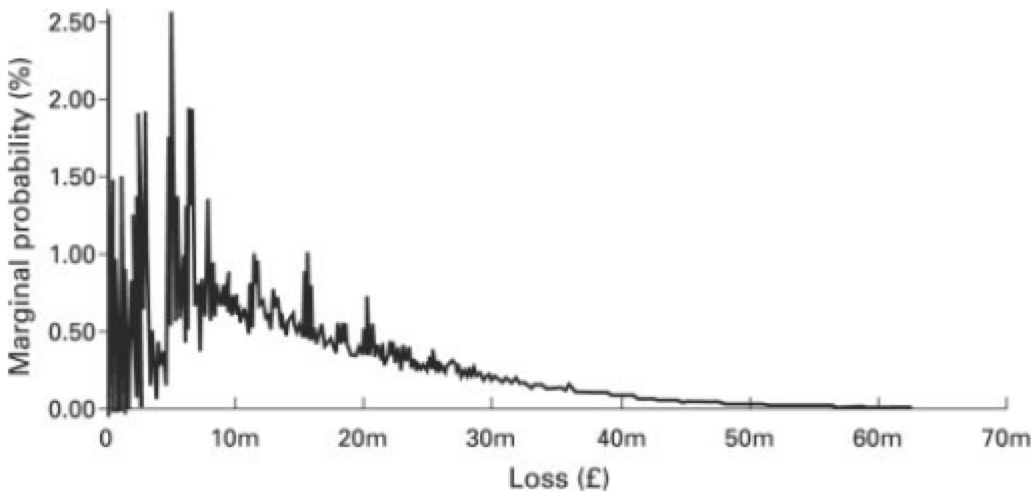
Table 6: Example default rate data (%)

Credit rating	*Mean default rate*	*Standard deviation*
A+	1.50	0.75
A	1.60	0.80
A–	3.00	1.50
BBB+	5.00	2.50
BBB	7.50	3.75
BBB–	10.00	5.00
BB	15.00	7.50
B	30.00	15.00

Table 7 : Obligor details

Company name	*Exposure* (£)	*Rating*	*Mean default rate* (%)	*Default rate standard deviation* (%)	*Sector split* *General economy* (%)
Co. (1)	358,475	B	30.00	15.00	100
Co. (2)	1,089,819	B	3.00	15.00	100
Co. (3)	1,799,710	BBB–	10.00	5.00	100
Co. (4)	1,933,116	BB	15.00	7.50	100
Co. (5)	2,317,327	BB	15.00	6.50	100
Co. (6)	2,410,929	BB	15.00	7.50	100
Co. (7)	2,652,184	B	30.00	15.00	100
Co. (8)	2,957,685	BB	15.00	7.50	100
Co. (9)	3,137,989	BBB+	5.00	2.50	100
Co. (10)	3,204,044	BBB+	5.00	2.50	100

Figure 12: Credit loss distribution



Chapter conclusion

This chapter outlined the different stages in the construction of a credit risk madel using the VaR approach as well as the quantification methods necessary for its development. To conclude our chapter, we wanted to take stock of the constraints and limitations that of such models.

The main constraint is the insufficiency of data, since the models are based on data estimated from historical data and not from real values, therefore no matter how sophisticated the model is, it will always have a margin of error that will tend to underestimate the risk.

The second constraint is the choice of parameterization: the bank must specify which parameter it will consider as random, but this approach is a bit subjective, as well as for the correlations between credit events, it is impossible to identify all these correlations within a credit portfolio.

Therefore, these models, like any other statistical model, are only a representation of reality built on the basis of a history, whose changing behavior can affect the results of these models.

Chapter 3: CreditRisk+ modeling applied to a corporate loan portfolio

Chapter introduction

In the previous chapters , we have reviewed the different theoretical aspects related to the modeling of credit risk and its general management. In this chapter we begin an empirical analysis with the aim of deriving the main risk measures, including the Value at Risk.

We have opted for a modeling by the CreditRisk+ model, the choice of this model was motivated by the many advantages that it presents and its adaptation to the Algerian banking sector.

Our modeling will be carried out on a portfolio of 428 loans granted by the Bank of Local Development (BDL) to companies of various sizes that operate in several sectors of the economy.

This chapter is divided into four sections:

First, we begin with a brief presentation of the Bank of Local Development (BDL), its history and its internal organization.

The second section is a general analysis of the selected sample in order to highlight the main characteristics of our portfolio.

Followed by a section dedicated to the definition of the parameters necessary for the CreditRisk+ modeling.

Finally, the last section presents, first, the way in which the sample data must be organized in order to introduce them in the official CreditRisk+ application, then we will analyse the results obtained from the modeling process represented by the different risk indicators, and finally we will end by running a few stress tests on our portfolio by simulating different unfavorable senarios and analyzing the impact of each one.

Section 1: Presentation of the host organization

1.1.History and Evolution of the BDL :

The bank of local development by abbreviation BDL was created following the restructuring of the Credit Populaire d'Algérie (CPA) by the decree N° 85/85 of April 30th 1985 in the form of a national banking institutuion intended for the financing and local development. On the basis of law 88/04 relating to the autonomy of the companies, the BDL gained autonomy and was transformed into a joint-stock company on February 20, 1989.

The share capital of the BDL was successively increased from 500 million dinars at its creation to 720 million dinars in 1994 in which the Treasury is the majority shareholder, in 1995 it rose to 1.440.000.000 dinars, then to 13.390.000.000 dinars in 2004, 15,800,000,000 dinars in 2010 and 36,800,000,000 dinars in 2017 and the Ministry of Finance is the Finance is the majority shareholder.

The BDL, had inherited in the beginning thirty-nine (39) agencies, a branch, a headquarters with a staff of seven hundred (700) agents, from the Crédit Populaire d'Algérie (CPA), within the framework of the restructuring of the financial sector. The start of the activity took place on July 1st 1985 while taking over the activities of the municipal credit banks (Caisses de Crédit Municipal) of Algiers, Oran and Constantine, grouped in a network of eight (08) branches including five (05) branches specialized in pawnbroking operations. The bank experienced a rough start, while trying to impose itself on a market already conquered by other banks of a great national scale namely the CPA, BNA and BEA. At that time the BDL has no IT tool neither at the central level nor at the level of the agencies, thus all operations had to be treated manually. On the other hand the creation of this bank coincided with the economic crisis that shook the country in 1986 due to the sudden drop in oil prices, which made its development uncertain with only two billion dinars of customer ressources , and one hundred thousand (100.000) customer accounts.

Currently the BDL has found its place in the Algerian banking market as the bank of SMEs in all sectors, liberal professions as well as the private individuals and households; It also attributes as much interest to the projects developed within the framework of employment assistance set up by the public authorities (ANSEJ, CNAC and ANGEM).

The head office of the Local Development Bank (BDL) is located at 5, rue Gaci Amar Staoueli-wilaya of Algiers, strong of its very extended network covering the entirety of the national territory through 156 agencies judiciously implanted among which 147 branches treating the usual banking operations (commercial agency) and two (2) annexes supervised by thirty-five (35) Commercial Poles supported by Size (16) Operational Poles with six (06) dedicated to pawnbroking, an activity for which BDL has exclusive rights.

1.2. Internal Organization of the BDL

During the internship, were were able to explore 3 main structures inside the bank which were:

- Structure for financing small and mid size companies (DASC)

- Structure for financing large companies (DGE)

- Structure for managing financial risks (DRF)

Figure 13: D.A.S.C Organizational Chart

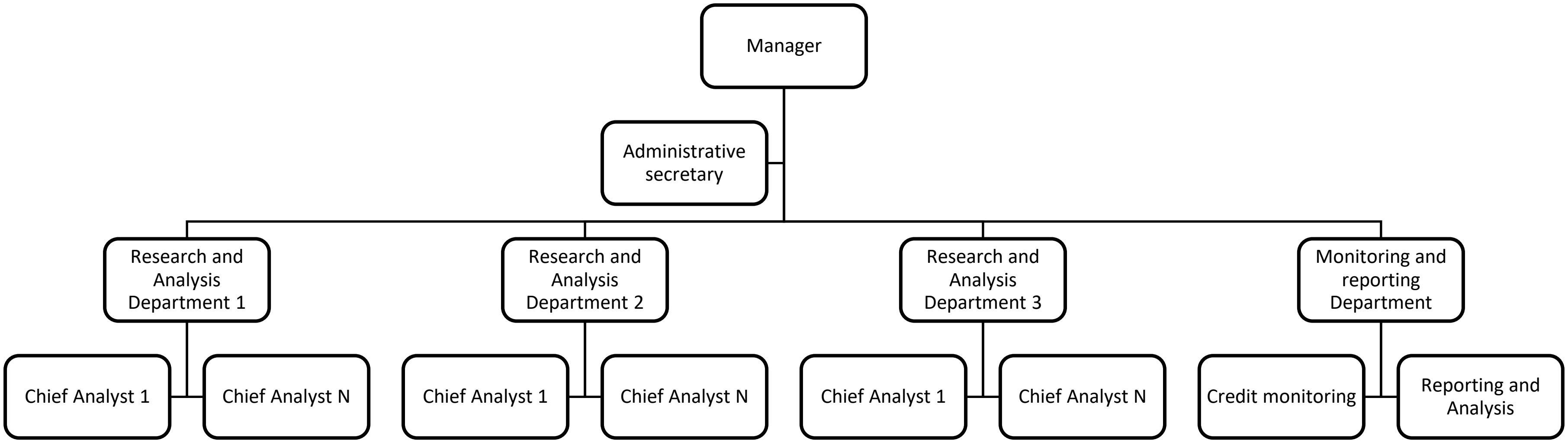


Figure 14: D.G.E Organizational Chart

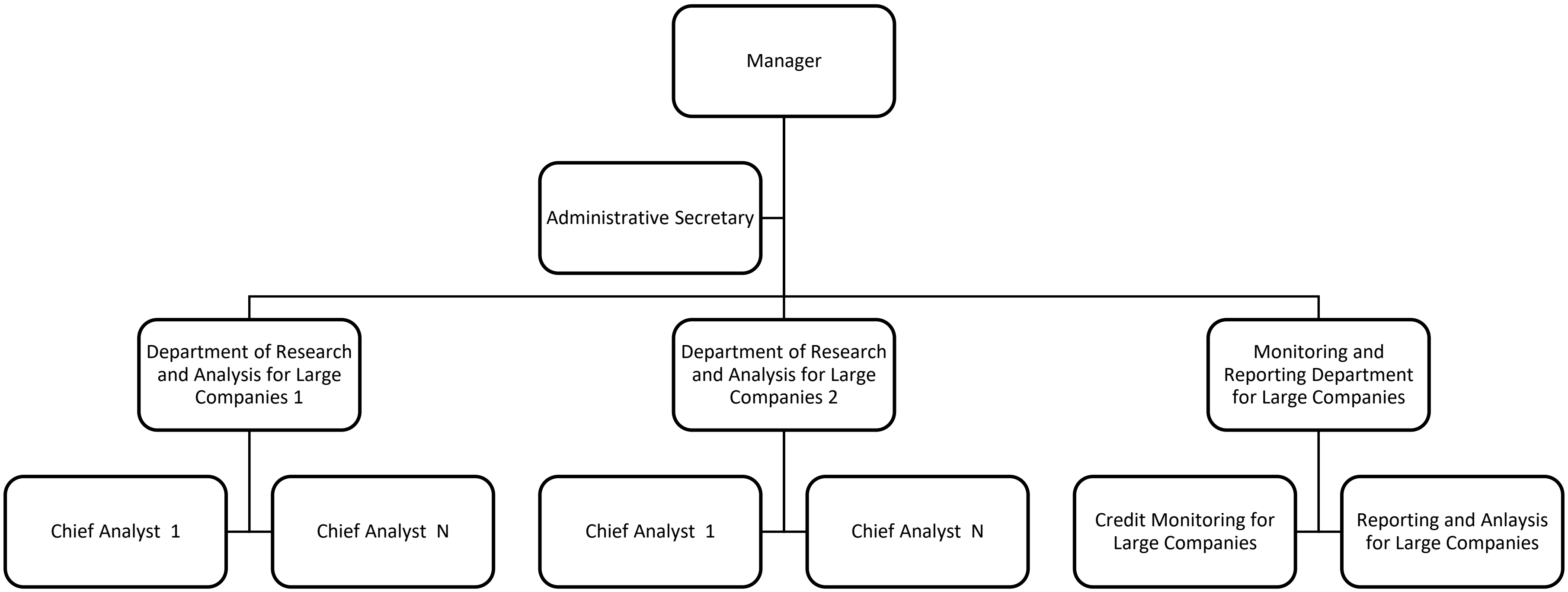
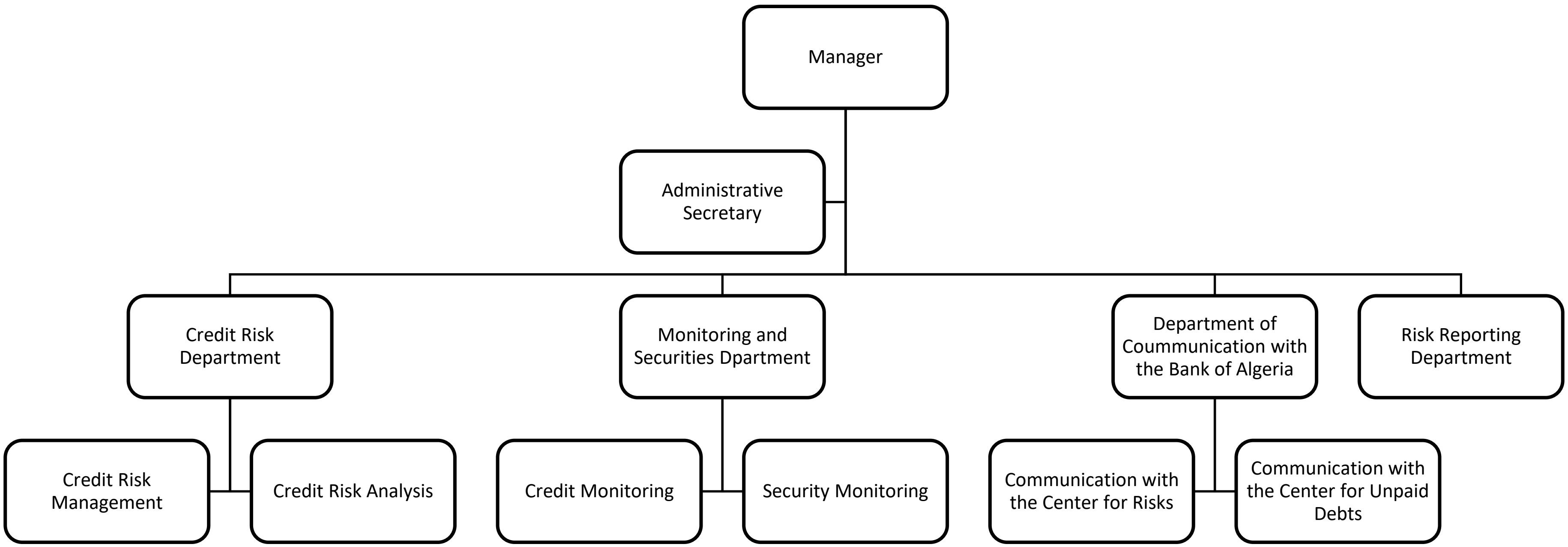


Figure 15: D.R.F Organizational Chart



Section 2: Exploratory analysis of the corporate credit portfolio

In this section, we will present the studied portfolio in a global way, study each variable in the database separately to highlight its contribution to the overall portfolio. Finally, we will make a synthetic analysis of the sample according to several criteria and aspects in order to better understand the financial and economic dimensions of the bank's portfolio.

2.1.Aggregate data

Our sample is a portfolio of loans to businesses and real estate developers given by BDL bank and observed on 31/08/2021. It consists of investment and equipment loans, , and real estate development loans.

The sample is composed of 428 loans spread throughout the territory national territory. The database includes the following information for each client:

- The sector of activity

- The legal sector

- The loan amount

- The interest rate

- The repayment periodicity

- Outstanding amount without arrears

- Outstanding amount with arrears

- The number of overdue payments

- Classification of the debt

- Date the loan was granted

- Duration of the loan in months.

- Amount and value of the guarantee

- Amount of uncollected interest

- Rate of provision

- Amount of the provision

- Presence or absence of mortgage

- Amount of financial guarantee

2.1.1. Quality of the database:

The database obtained is characterized by a missing value rate of 8.13%.

The treatments performed on the database were:

- Deletion of lines that do not contain the amount of funds unlocked , given the crucial importance of this data in the calculation of default probabilities.

- Filling in all the lines that do not contain a repayment period by a quarterly repayment, as in the case for the vast majority of corporate loans.

- Deletion of columns that are not necessary for our work.

- Exclusion of syndicated loans due to their specific treatment.

-Exclusion of consolidated loans due to their specific treatment.

2.2.Portfolio Description

The following is a description of the variables collected:

2.2.1. Amount granted:

The loan amount represents the volume of the client's contractual commitment to his bank.. The bank accepts or declines to grant the loan depending on the quality of the borrower which is determined following a study of their submitted paperwork and financial statements in order to evaluate their capacity ro reimbourse the loan in its entirety.

Table 8: Descriptive statistics for the intervals (Amount)

Lower bound	Upper bound	Frequency	Relative frequency
0	1,100,000,000	383	0.895
1,100,000,000	2,200,000,000	28	0.065
2,200,000,000	3,300,000,000	9	0.021
3,300,000,000	4,400,000,000	0	0.000
4,400,000,000	5,500,000,000	1	0.002
5,500,000,000	6,600,000,000	2	0.005
6,600,000,000	7,700,000,000	1	0.002
7,700,000,000	8,800,000,000	1	0.002
8,800,000,000	9,900,000,000	1	0.002
9,900,000,000	11,000,000,000	2	0.005

Source: XLSTAT

We note that :

- loans with a volume of less than 1.1 billion dinars represent 89.5% of the portfolio.

- The higher the amount requested, the more the number of favorable opinions of agreement decrease. Indeed, the risk incurred increases with the increase in the volume of the commitment. In addition, the bank is bound by concentration limits.

Table 9: Descriptive statistics (Loan Amount)

Statistic	Amount
Nbr. of observations	428
Minimum	200,000
Maximum	10,760,100,000
Sum	191,006,300,000
Amplitude	10,759,900,000
1st Quartile	7,000,000
Median	34,150,000
3rd Quartile	348,250,000
Mean	446,276,402
Standard deviation (n-1)	1,173,174,851

Source:XLSTAT

Our reading of the table above allows us to make the following observations:

- The sum of the 428 credits granted is 191 006 300 000 DZD, representing the total commitment of the clients in this portfolio towards the bank.

- The smallest amount of credit in the portfolio is 200 000 DZD , granted to a small retailer.

- The highest credit amount in the portfolio is 10 760 100 000 DZD , granted to a private real estate developer.

-The difference between these two amounts is equal to the amplitude of the variable which is 10 759 900 000 DZD. This difference, which is considerable, reflects the rather high dispersion of the amounts of the granted loans, and shows that the bank has a diversified range of customers in their needs of financing.

- 25% of the credit amounts are below 7 000 000 DZD (1st quartile), and 75% of the amounts are below 348 250 000 DZD (3rd quartile).

- The average amount of loan granted is 446 276 402 DZD, while the standard deviation is 1 173 174 851 DZD. This deviation is relatively high since it exceeds the average, which reflects a low concentration of observations around their average and shows, once again, the high dispersion of the variable.

2.2.2. Sector of activity

The clients in our portfolio are classified in the following sectors of activity:

• **Services**: includes companies providing various services.

• **Agri-food**: includes companies that operate in activities related to agriculture, all forms of agriculture, all forms of animal husbandry, as well as all activities that produce unprocessed unprocessed food raw materials. The processing of live products plants or fruits into finished food products is also included in this sector.

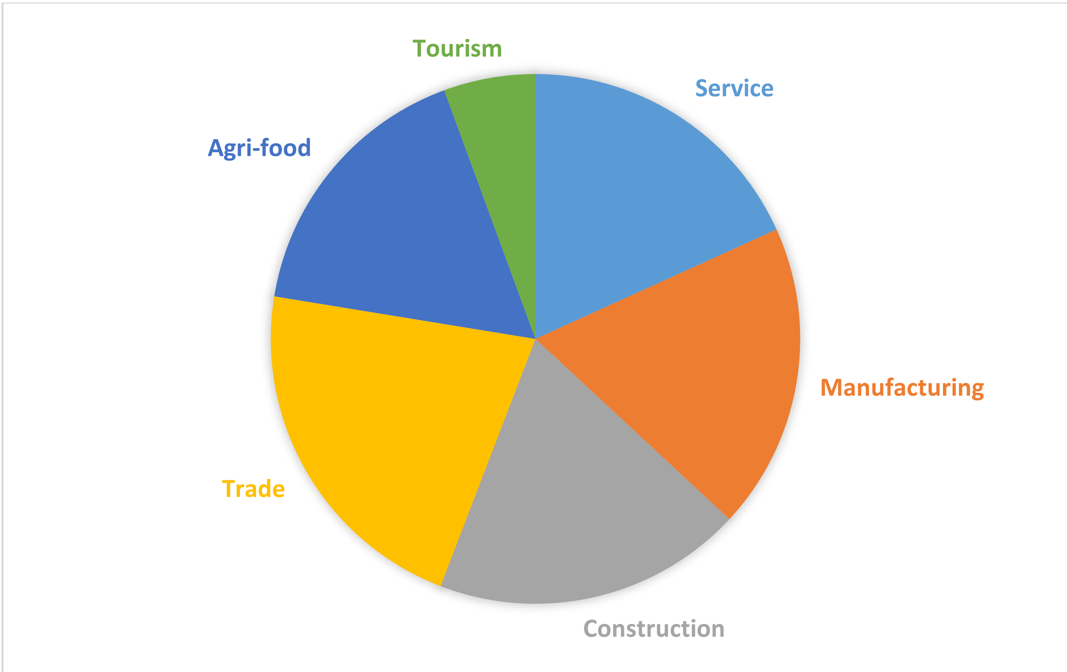
• **Manufacturing** : includes all enterprises that are active in the mechanized and concentrated production of all forms of goods as well as the transformation of raw materials into finished products.

• **Construction**: includes companies of civil engineering, building, public works and hydraulics. hydraulic engineering.

• **Commercial activity (Trade)** : includes all companies whose main vocation is the purchase and sale; detailed or wholesale, of goods, as well as companies import/export of consumer goods.

• **Tourism**: companies which provide the products and services that are meant and used by tourists at different stages of travel and tourism.

Figure 16: Portfolio distribution by sector



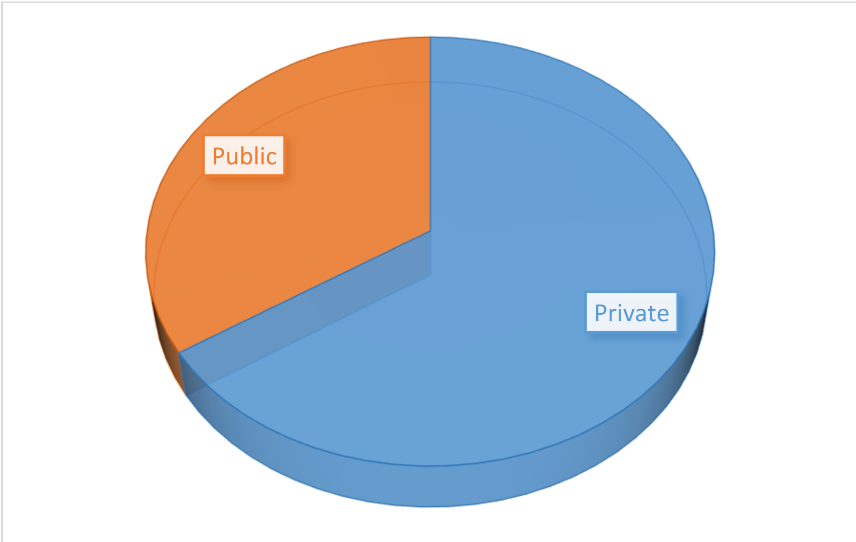
Our portfolio of corporate loan is mostly well balanced when it comes to the clients' sector of activity, we note that the share of total loan volume is around 17% to 18% for the service, manufacturing, construction, and agri-food sectors. The trade sector presents a slight edge with a share of 22% of total loan volume, while the tourism sector lags majorly behind with only around 6% of total loans.

This analysis shows the efforts made by the bank to diversify and balance its portfolio while also highlighting the lack of development of the tourism sector in the country.

2.2.3. Legal status

Each line of credit in our portfolio is destined towards either the public or private sector. The breakdown of our portfolio is as follows:

Figure 17: Portfolio distribution by legal status



2.2.4. Unpaid capital

The unpaid capital represents the loss due to the occurrence of a default event of the borrower at a given date and intensity.

Note here that the "unpaid" variable is the sum of the two variables: unpaid principal and uncollected interest.

Table 10: Descriptive statistics (Unpaid)

Statistic	Unpaid
Nbr. of observations	428
Minimum	0
Maximum	538,005,000
Sum	3,833,599,000
Amplitude	538,005,000
1st Quartile	0
Median	0
3rd Quartile	640,000
Mean	8,957,007
Standard deviation (n-1)	40,441,843

Our reading of the table above leads us to make the following observations:

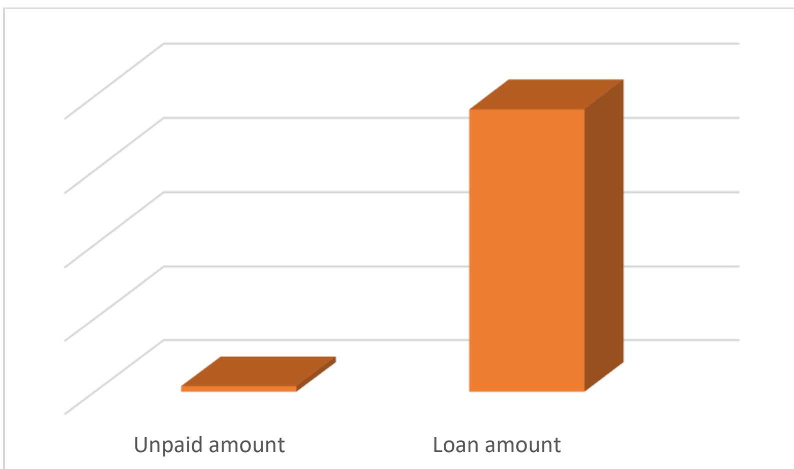
- The minimum amount of unpaid capital noted on the whole portfolio is 0 DZD, on a total of 264 observations, i.e. 62% of the clients in this portfolio have not recorded any unpaid bills at the close of 31/08/2021. The bank has noted that 38% of the clients in the portfolio had at least one outstanding payment.

- The most important unpaid capital in the portfolio is of 538 005 000 DZD and relates to the same client that was granted the largest loan amount.

- The difference between the two extremes of the unpaid amounts gives us the amplitude of the variable which is 538 005 000 DZD.

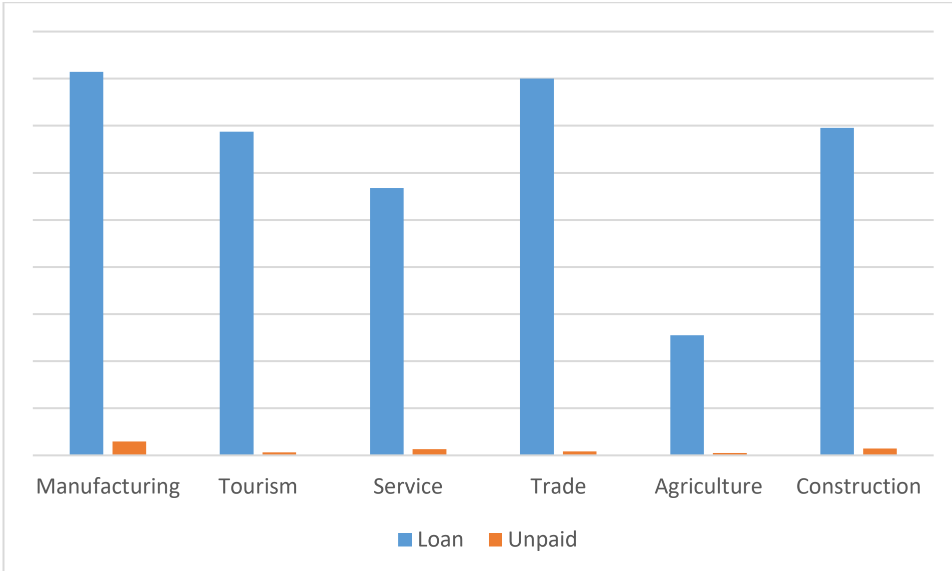
- The average unpaid amount is 8 957 007 DZD

Figure 18: Unpaid capital relative to total loan volume



The graph above shows that the total outstanding loans recorded in this portfolio amount to **2%** of the total loans granted.

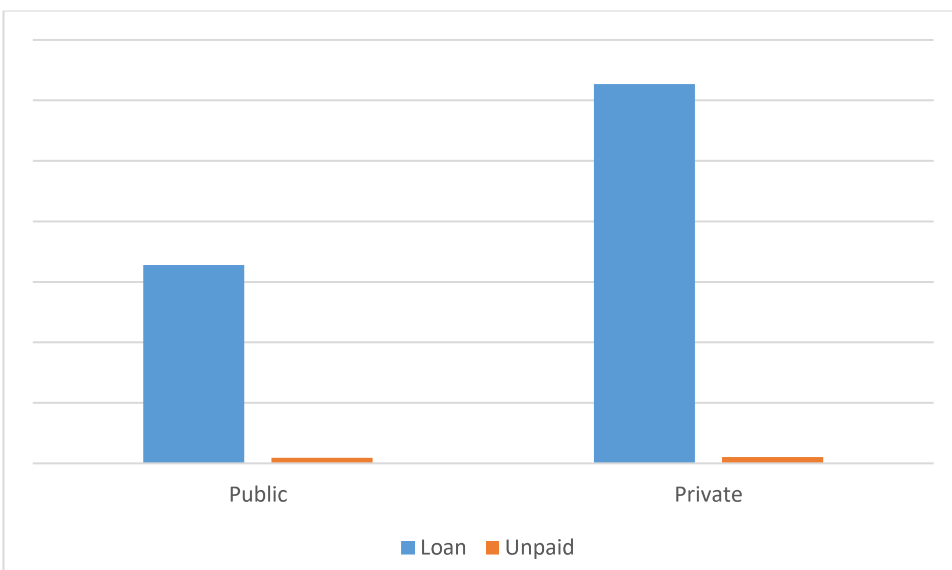
Figure 19: Unpaid capital relative to total loan volume by sector



The volume of unpaid bills in each sector of activity is proportional to the volume of credit granted.

The percentage of unpaid capital to total loaned amount is the highest in the manufacturing sector at around 4%, but remains well within the acceptable range.

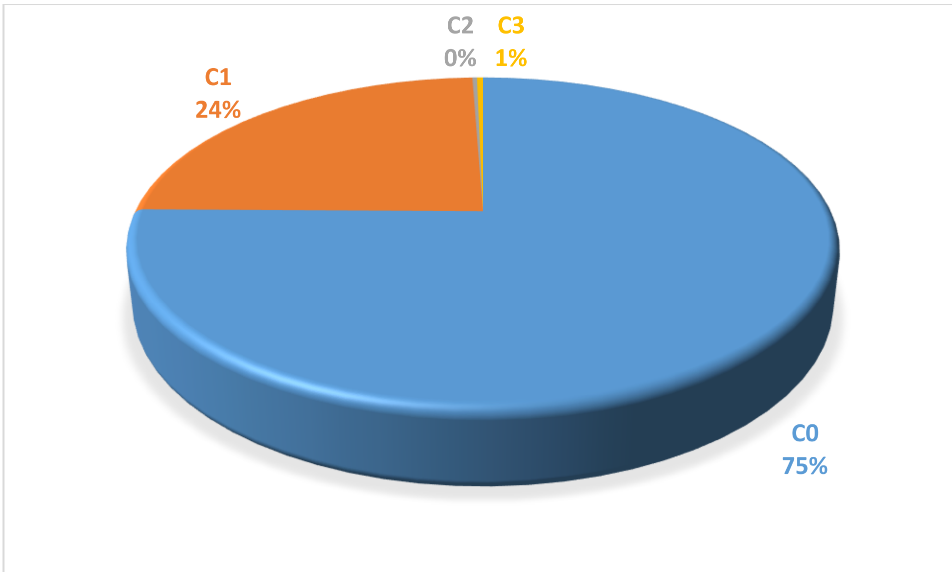
Figure 20: Unpaid capital relative to total loan volume by legal status



The proportion of unpaid bills in the private sector is 2% and 3% in the public sector. Although this single-digit proportion remains acceptable.

2.2.5. Risk class

Figure 21: Breakdown of the portfolio into risk classes



¾ of the portfolio (75%) consists of current "C0" receivables. The remaining quarter is dominated by "C1" incertain loans with a share of 24%.

At this stage, it seems appropriate to make a crucial point about the classification of companies into risk classes. During our internship, we learned that companies escape the systematic classification when they default on payment

Indeed, BDL bank considers the claims to companies as commitments of a particular nature, which gives them a specific treatment in terms of deadlines and flexibility of the relationship.

This is why there is a committee in charge of deciding the situation of the companies after a case-by-case study, it is required to provide parallel arguments for the of the decision to classify, especially for the justification to the auditor.

This is the reason why some receivables are classified as "C0" despite the fact that number of unpaid installments.

Section 3: Estimation of the model parameters

This section can be considered as the core of our test. It aims to provide the risk andand accounting parameters required in the modeling of our portfolio.

The credit risk modeling process goes through many steps; first, credit risk should be estimated at the individual level, then aggregated through athrough a portfolio approach. All of this is done with the help of several tools and software.

3.1.Credit risk at the individual level

The measurement of credit risk at the individual level involves the estimation of its threeparameters, i.e., the Probability of Default (PD), the Loss Given Default (LGD) and the Exposure at Default (EAD), for each credit line.

3.1.1. Probabilities of default (PD)

3.1.1.1. Classification of clients

In our default intensity approach, the customer can be classified according to his creditworthiness into two possible categories: default or non-default. Let us consider the Bernoulli indicator variable Yt representing the event of default by the customer on his debt to the bank over a time horizon T.

$$Y_t = \begin{cases} 1 & \text{if default} \\ 0 & \text{if not} \end{cases}$$

Here we are faced with the need to determine the notion of default itself.

In the field, classifying a client in the "default" category following an initial non-payment may be unfair and irrational with regard to certain clients who may be usually "good" and who will be placed in the same category as doubtful customers.

It is important to note that changing a client's classification is not a trivial act insofar as it involves a whole process of changing procedures and calculating provisions rescheduling in the bank's internal systems, etc.

This idea is in line with the strategy of the BDL concerning the processing of corporate loans in terms of monitoring commitments developed previously. After discussions with with the personnel during the training course, it was agreed to retain for this work a default threshold of two unpaid installments for a quarterly repayment frequency:

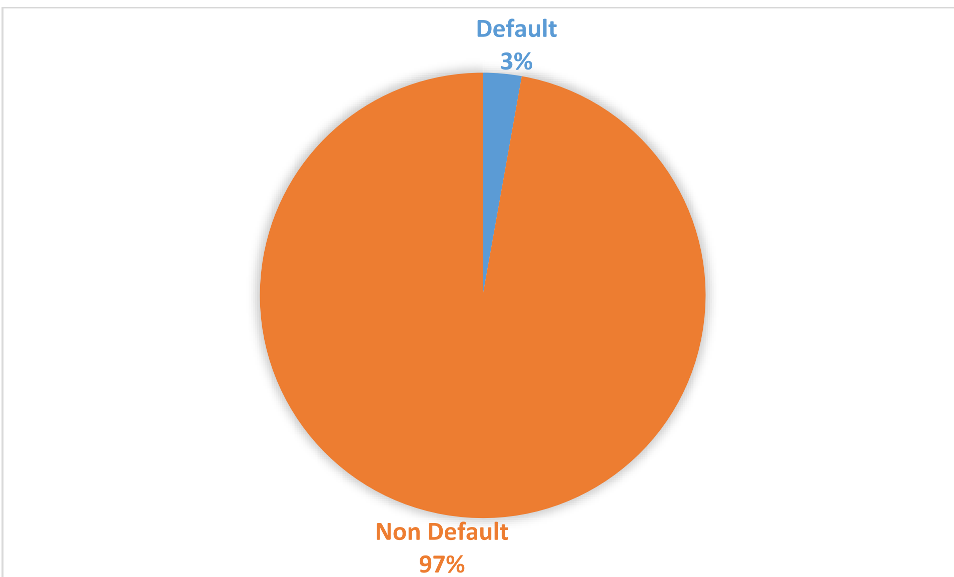
default threshold θ = 2

Our Bernoulli indicator variable modeling the default event then takes the following form:

$$Y_t = \begin{cases} 1 & \text{if } N(t) \geq 2 \\ 0 & \text{if } N(t) \leq 2 \end{cases}$$

We proceeded to the classification of all the clients of our portfolio according to the chosen criterion. These are the results obtained:

Figure 22: Portfolio classification based on default criteria



The number of clients in default according to the chosen criteria is 12, or 3% of the total, while clients classified as non-defaulting numbered 416, or 97% of the total.

Note that if we had classified clients according to a binary variable that considers the client in default only after a single unpaid bill, the number of clients in default would be much higher.

This is why the choice of the default barrier is a crucial element, insofar as it impacts bank profitability by impacting the amount of provisions made.

3.1.1.2. Adjustment of the distribution of the default.

The calculation of default probabilities requires knowledge of the distribution of the event, in this case default, represented by the "number of unpaid installments".

The default intensity approach models the default by the first jump of a Poisson process. It is therefore imperative to verify the possibility of approximating the empirical distribution of the number of delinquencies observed in our database by the theoretical poisson distribution.

A technique using "Easyfitt" software consists in analyzing the empirical distribution and to bring it closer to the most suitable theoretical distribution by ranking the various options on the basis of the Anderson-Darling and Kolmogorov-Smirnov test.

The results of the fitting are illustrated below:

Table 11: Goodness of Fit - Summary

#	**Distribution**	**Kolmogorov Smirnov**		**Anderson Darling**	
		Statistic	Rank	Statistic	Rank
1	D. Uniform	0.66667	1	371.89	3
2	Geometric	0.76703	3	304.7	2
3	Poisson	0.73805	2	272.87	1
4	Bernoulli	No fit (data max > 1)			
5	Binomial	No fit			
6	Hypergeometric	No fit			
7	Logarithmic	No fit (data min < 1)			
8	Neg. Binomial	No fit			

Source: EasyFit

Figure 23: Probability density functions (Sample and Poisson)

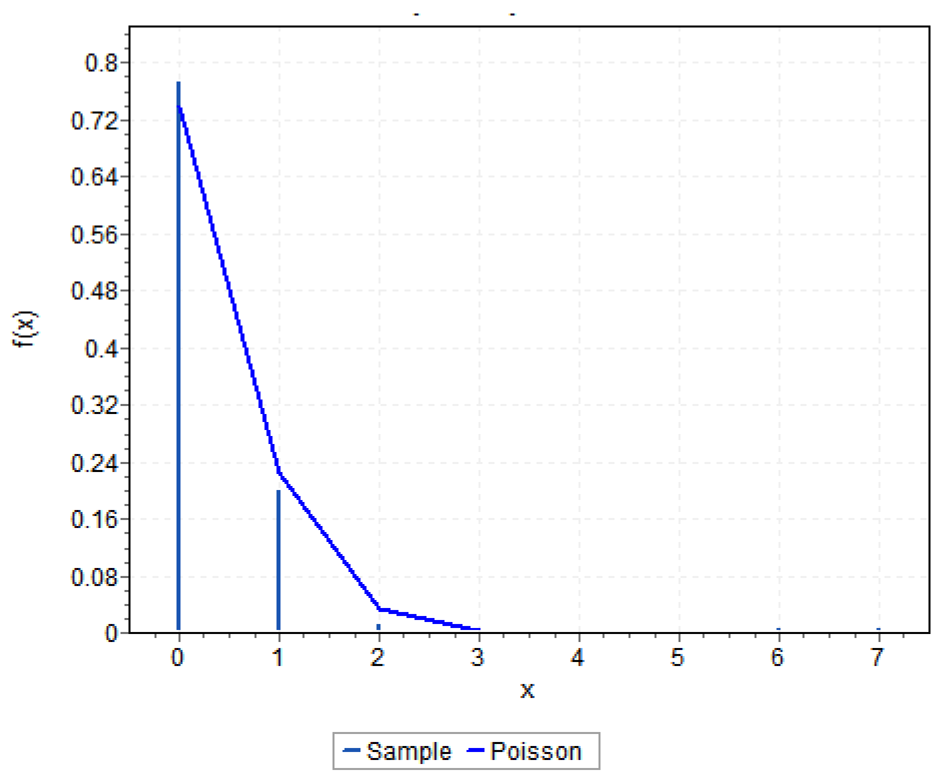
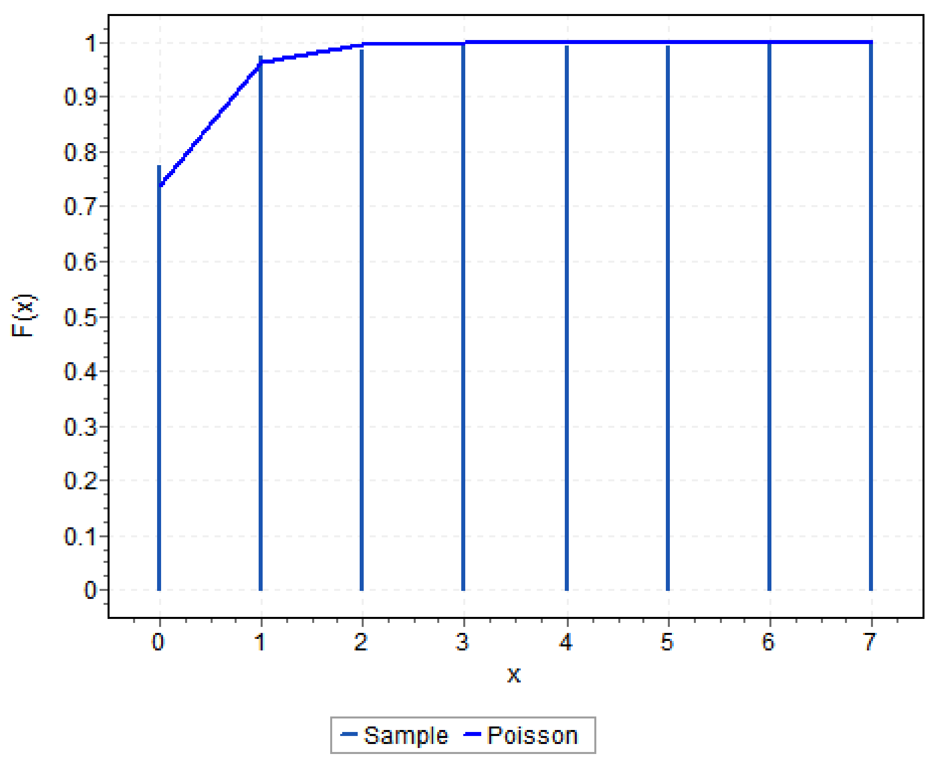


Figure 24: Cumulative Distribution Functions (Sample and Poisson)



We notice that the Poisson distribution is the second most common distribution that best approximate our empirical data according to the Kolmogorov Smirnov test and the very best according to the Anderson Darling test. The quality of the fit is not optimal but is still usable, we believe that this is due to the non-exhaustiveness of our database and the existing missing values.

3.1.1.2. Estimation of default intensities

The Poisson distribution is a discrete probability distribution that describes the behavior of the number of events occurring in a fixed time interval with a known average frequency λ.

The event being counted in our case is "default" and its frequency is the intensity of the borrower's default during the period between the date the loan was granted and and the portfolio observation date.

$$N(t) \sim P(\lambda)$$

$N(t)$: The number of defaults between [0, t].

The default intensity can therefore be calculated according to the following formula:

$$\lambda_t = \frac{N(t)}{\Delta t}$$

Δt: the time between [0, t], i.e., between the date the loan was granted and the date the date of observation of the portfolio.

Table 12: Calculation of default intensities

Loan n°	Date of approval	Δt	Δt in years	λ
1	03-03-20	546	1.495890	0
2	26-11-16	1739	4.764384	0.20989074
3	05-03-19	910	2.493151	0
4	07-03-17	1638	4.487671	0
5	22-10-17	1409	3.860274	0
6	05-09-17	1456	3.989041	0.25068681
7	06-03-18	1274	3.490411	0.28649922
8	03-03-20	546	1.495890	0
9	12-02-17	1661	4.550685	0
10	07-03-17	1638	4.487671	0
11	01-09-20	364	0.997260	1.00274725

12	03-09-19	728	1.994521	0.50137363
13	05-03-19	910	2.493151	0.4010989

Table 13: Descriptive statistics of the "default intensity" variable

Statistic	λ
Nbr. of observations	428
Minimum	0.000
Maximum	2.407
1st Quartile	0.000
Median	0.000
3rd Quartile	0.000
Mean	0.130
Variance (n-1)	0.100
Standard deviation (n-1)	0.316

We note that 75% of borrowers have a default intensity equal to zero.

Since the probability of default depends on its intensity, this finding is consistent with one of the of the default intensity model, which states that there is a very large number of borrowers for whom the probability of default is very low.

3.1.1.3. Default probabilities estimation

Reminder that :

$$Y_t = \begin{cases} 1 & \text{if } N(t) \geq \theta \\ 0 & \text{if } N(t) < \theta \end{cases}$$

The probability of default for a customer i can therefore be formulated as follows:

$$\begin{aligned} PD_i = E(Y_t) &= 1 * P(N(t) \geq \theta) + 0 * P(N(t) < \theta) \\ &= P(N(t) \geq \theta) = 1 - P(N(t) < \theta) \end{aligned}$$

And since the number of defaults follows a Poisson distribution, we can assume that :

$$PD_i = 1 - \sum_{k=0}^{\theta-1} \frac{e^{-\lambda t}(\lambda t)^k}{k!}$$

Generally, the study horizon that is used to estimate this probability of default is one year (t = 1). This allows us to write :

$$PD_i = 1 - \sum_{k=0}^{\theta-1} \frac{e^{-\lambda}(\lambda)^k}{k!}$$

Table 14: Descriptive statistics of individual probabilities of default

Statistic	PD
Nbr. of observations	428
Minimum	0.000
Maximum	0.693
1st Quartile	0.000
Median	0.000
3rd Quartile	0.000
Mean	0.028
Variance (n-1)	0.007
Standard deviation (n-1)	0.084

- The lowest probability of default is 0% observed for 331 credit lines, i.e. 77.34% of our portfolio.

- The highest probability of default is 69.30% observed in with with a history of 6 unpaid installments since the credit was granted in 2019.

- The portfolio's default probabilities have an average of 2.8%.

It is important to remember that the probability of default PD depends directly on the default intensity λt which in turn depends directly on the number of defaults.

This is why we observe default probabilities even for clients classified as "non-default". At least one first default has been observed among these customers, even though they have not yet reached the default threshold θ chosen, hence the appearance of a default intensity for these customers.

We note, however, that the probability of default for clients in "non-default" status remain very low compared to those who have crossed the default threshold.

3.1.1.4. Validation of the model

The "probability of default" variable varies in the same direction as the "number of non-payements" variable: A debt with a large number of unpaid installments in the past will have a high probability of default in the future. Indeed, this is a direct and positive relationship that can be verified empirically through a simple linear regression of N(t) on PD by the ordinary least squares method. The results of the regression are shown below:

Table 15: Model parameters (PD)

Source	Value	Standard error	t	Pr > |t|	Lower bound (95%)	Upper bound (95%)
Intercept	0.000	0.002	-0.142	0.887	-0.004	0.004
Nb_unpaid	0.094	0.003	37.301	**<0.0001**	0.089	0.099

The estimated model is :

PD = -0.00030202 + 0.09412025 *nb_unpaid

The results show a regression coefficient significantly different from 0 under the hypothesis H0: a=0. Indeed, the empirical value of Student's t is greater than the t read in the table at the 5% significance level. Also, the critical probability is lower than 5%, which allows us to reject the H0 hypothesis.

After validating the significance of the estimated coefficient, we need to measure the quality of our regression using the analysis of variance equation:

$$\sum_t (y_t - \bar{y})^2 = \sum_t \left(\hat{y}_t - \bar{\hat{y}}_t\right)^2 + \sum_t e_t^2$$

$$SST = SSR + SSE$$

Table 16: Analysis of variance (PD)

Source	DF	Sum of squares	Mean squares	F	Pr > F
Model	1	2.326	2.326	1391.390	**<0.0001**
Error	426	0.712	0.002		
Corrected Total	427	3.038			

The previous equation allows us to judge the quality of the fit of a model. Indeed, the closer the the explained variance is to the total variance, the better the fit of the scatter plot by the least squares line.

It is usual to calculate the following ratio:

$$R^2 = \frac{\sum_t (\hat{y}_t - \bar{y})^2}{\sum_t (y_t - \bar{y})^2} = 1 - \frac{\sum_t e_t^2}{\sum_t (y_t - \bar{y})^2}$$

Table 17: Goodness of fit statistics (PD)

Observations	428
Sum of weights	428
DF	426
R^2	0.766
Adjusted R^2	0.765
MSE	0.002
RMSE	0.041
MAPE	124.995
DW	2.030
Cp	2.000
AIC	-2734.687
SBC	-2726.569
PC	0.237

In our case, the R_2 is equal to 76.6% . This figure provides information on the propensity of the the variable "number of non-payements" in the explanation of the variable "probability of default". The remaining 23.4% are explained by other indeterminate variables.

Overall, we can affirm the existence of a significant relationship between the number of historical defaults and the chance that the individual will default in the future as estimated by our model.

3.1.2. The Loss Given Default (LGD)

In the absence of data concerning the flow of recovery for each line of credit, we were unable to estimate the recovery rate by studying its own distribution We will settle for a simplistic approach that considers the guarantee as the certain recovery of the bank in case of default.

In our database, each line is characterized by the presence or absence of a mortgage and/or a financial guarantee. By taking into consideration the deduction ratios of the guarantees we can approximate the recovery rate for each line by the following formula:

$$RR_i = \frac{50\% * \text{ Value of the mortgage } + 80\% * \text{ Value of the financial security}}{\text{Total owed}}$$

$$LGD_i = 1 - RR_i$$

Table 18: LGD calculation for each line of credit (extract)

Line	*Total owed*	*Mortgage*	*Fin Security*	*Recovery*	*RR*	*LGD*
1	129,800,000	144,200,000	0	72,100,000	0.55546995	0.444530046
2	372,400,000	458,226,000	0	229,113,000	0.61523362	0.38476638
3	1,189,200,000	1,319,580,150	1,704,000	661,153,275	0.55596475	0.444035255
4	282,700,000	292,591,700	21,542,045	163,529,486	0.57845591	0.421544089

3.1.3. Exposures at Default (EAD)

This parameter has been provided directly in our database under the name “Total owed” The variable is made up of the outstanding principal plus the amount of unpaid bills, if any.

3.2.The portfolio approach to credit risk

The construction of the loss distribution function "PDF" is the common goal of all portfolio models despite the disparity of their approaches. Obtaining this distribution will allow to quantify the credit risk at different confidence thresholds and to obtain very valuable aggregates in the modeling process. The imperative of a portfolio approach stems from the fact that the total risk incurred is not obtained by adding up the individual risks that make up the portfolio, due to the interference of diversification and correlation phenomena between individuals.

3.2.1. Adaptation of individual default probabilities

In order to model the credit risk of a portfolio, Creditrisk+ requires the introduction of exposures into risk classes, in other words, ratings. Then, the default probability of each class as well as the related standard deviation are assigned to the individuals belonging to the same risk class.

At this stage, we are faced with the need to classify our portfolio into risk classes. Two questions arise:

► What is the number of classes to construct?

► What are the probabilities that delimit each class?

In truth, there is no rule that answers these two questions, so the choice is left to the each bank according to the expected objectives of its rating system and its segmentation needs. However, for the purposes of our work, we have chosen to allocate the portfolio on the basis of a "mapping" based on the ratings published by the Standard and Poor's rating agency for the year 2020 .

Note that the information published by the rating agencies is obtained by studying the history of several borrowers over several years (weighted long term average) . This correspondence will therefore allow us to exploit this wealth of data.

Table 19: S&P 2020 Global Corporate Annual Default Rates By Rating Category

Rating	Default rates	Standard Deviation
AAA	0	0
AA	0.02	0.07
A	0.05	0.1
BBB	0.16	0.25
BB	0.63	0.99
B	3.34	3.24
CCC	28.3	11.79

Source:S&P Global

It is now necessary to delimit the boundaries of each class in order to carry out the allocation of our portfolio. To do this, we have used a simple arithmetic method which consists in allocating each line of credit to the rating which mean default rate is closest to its Probability of Default. The assignment of the individuals is then possible thanks to a nested "IF" function.

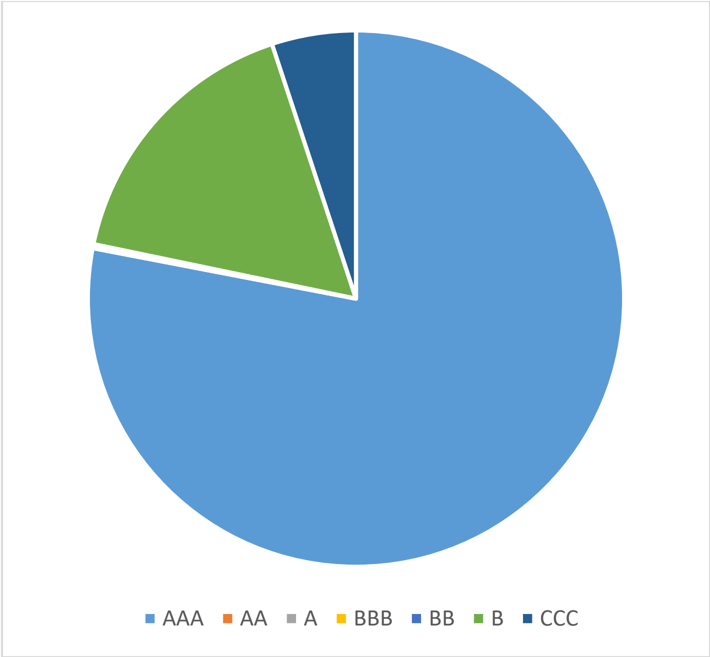
Table 20: Assignment of individuals in the portfolio into risk classes (Extract)

Line	PD	Rating	Mean default rate	Std Dev
1	0.595479308	CCC	0.283	11.79
2	0.026632882	B	0.0334	3.24
3	0	AAA	0	0
4	0.021429701	B	0.0334	3.24
5	0	AAA	0	0
6	0.265251774	CCC	0.283	11.79

Table 21: Portfolio segmentation by risk class

RATING	AMOUNT
AAA	323
AA	0
A	0
BBB	0
BB	1
B	69
CCC	21

Figure 25: Portfolio segmentation by risk class



Section 4: Modeling of credit risk

The modeling of credit risk will allow us to generate two main parameters , namely the Expected Loss (EL) and the Unexpected Loss (UL). To do this we will use the software Creditrisk+ a default model more adapted to credit risk. It takes the form of a simplified application of MS Excel created by Credit Suisse First Boston.

4.1.Presentation of the creditrisk application

The CreditRisk+ application comes with a Microsoft-Excel workbook with an additional macro macro that allows easy handling of portfolios containing up to 4000 loans. This workbook consists of eight (8) worksheets:

-The first sheet called "Control page" is a control page that provides access to the multiple functionalities of the credit risk management model;

- The second sheet, "Exposure & Static Data", is used to save the data (exposure, volatility and default rate);

- Pages 3 to 7 contain illustrative examples of the options for using this application;

- The eighth sheet "Blank Template" is a blank page where we introduce our data (inputs) in order to use the model.

4.2.Model inputs

The inputs to a credit risk model are:

- The probability of default (PD);

- The volatilities of default rates expressed by standard deviations (SD);

- Loss given default (LGD);

- Net exposure at default (EAD = EAD*LGD);

- The sectors of activity.

4.2.1. Net Exposure At Default:

Net exposure at default reflects the bank's true risk exposure on a specific loan after taking into account the amount that can be recovered at default through liquidating the collateral.

Table 22: Calculating Net exposure (extract)

EAD	LGD	Net Exposure
3,888,850,000	0.206349115	802,460,754
1,425,270,000	0.142857143	203,610,000
720,800,000	0.362975166	261,632,500
1,672,990,000	0.019164717	32,062,380
2,391,000,000	0.298563363	713,865,000
2,268,000,000	0.338624339	768,000,000
488,775,000	0.125962073	61,567,112
1,590,120,000	0.110130053	175,120,000

Once we have all the inputs in our possession, we will proceed to the introduction of the data in the "Blank Template" page, as shown in the extract below:

Table 23: Extract from data introduced into CreditRisk+ software

					Sector split					
Name	**Exposure**	**Rating**	**Mean Default rate**	**Standard Deviation**	**Manufacturing**	**Service**	**Trade**	**Construction**	**Tourism**	**Agri-food**
1	802460754	AAA	0.00%		0.00%	100.00%	0.00%	0.00%	0.00%	0.00%
2	203610000	AAA	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
3	261632500	CCC	28.30%	11.79%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
4	3121.1	B	3.34%	3.24%	100.00%	0.00%	0.00%	0.00%	0.00%	0.00%
5	32062380	B	3.34%	3.24%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
6	713865000	B	3.34%	3.24%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%
7	768000000	AAA	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%
8	61567112.1	B	3.34%	3.24%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%

Once the data is inserted, we just have to click on the "Activate Model" button and a dialog box appears asking us to specify the different data fields that contain the modeling inputs (net exposure, average default rate, default rate volatility...) as well as the cells containing the modeling outputs (risk contributions, quantiles and loss distribution). This dialog box also allows us to choose the confidence threshold required.

4.3.Model outputs

Thanks to the VBA application " Visual Basic for Applications " with which the model is equipped, it automatically calculates the loss distribution, quantiles, expected losses and the risk contributions .

4.3.1. Loss distribution:

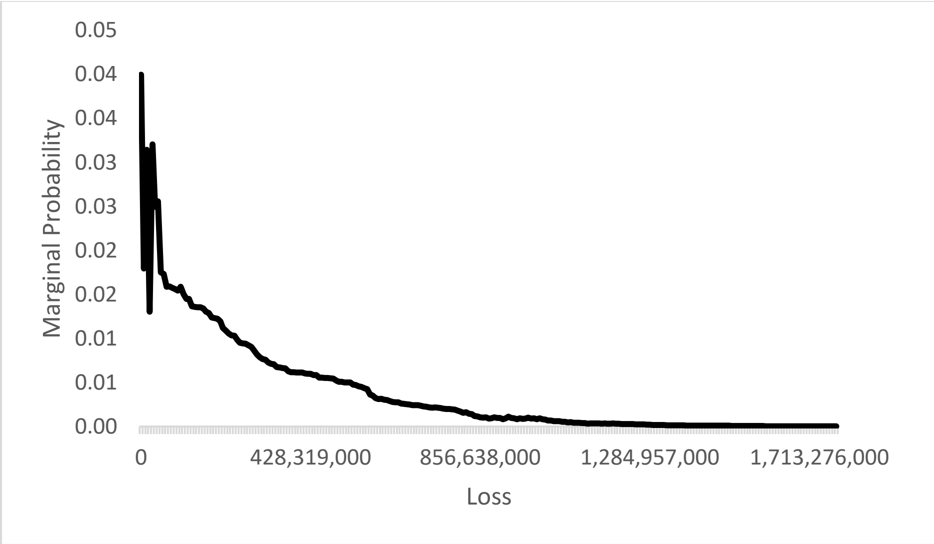
The CrediRisk+ application will decompose the portfolio to multiples n of the exposure unit L. The latter is chosen by the model automatically, it is equal in our case to 7 138 650 DZD (L=7 138 650. Thereafter this application associates to each amount (nL) a corresponding probability with n = 0, 1,...,246. The table below is an extract of the of the loss distribution calculation:

Table 24: Loss distribution calculation (Extract)

Name	Credit loss amount	Probability
1	0	3.995%
2	7,138,650	1.793%
3	14,277,300	3.144%
4	21,415,950	1.303%
5	28,554,600	3.205%
6	35,693,250	2.494%
7	42,831,900	2.559%
8	49,970,550	1.750%
9	57,109,200	1.732%

The loss distribution is graphically translated as follows:

Figure 26: Portfolio credit loss distribution



The shape of our empirical loss distribution approaches the theoretical shape of the credit loss distribution. Indeed, the absence of skewness and kurtosis coefficients of the model's outputs leads us to rely on the visualization of the graph. This reveals a strong asymmetry spreading the curve to the right with a thick tail while being more pointed from the top than a normal distribution. It is therefore "left kewed" and "leptokurtic" like the theoretical "PDF".

4.3.2. The main quantiles of the loss distribution:

The "Creditrisk+" model allows to calculate the Value-at-Risk (VaR) at different levels of confidence as shown in the table below:

Table 25: Value at Risk Calculation

Percentile	Credit loss Amount
Mean	292,360,082
50	242,107,232
75	420,309,509
95	807,578,566
98	974,823,596
99	1,164,041,678
99.5	1,298,226,557
99.8	1,448,096,239
99.9	1,631,215,874

The confidence level chosen is 99.9%, from this table we can extract the following results:

VAR = 1 631 215 874 DZD

EL = 292 360 082 DZD

UL = 1 338 855 792 DZD

4.3.2.1. Interpretation of results:

A. The Expected Loss

The expected loss is the amount that the bank is likely to lose on average on its credit portfolio over a given time horizon. In our portfolio, for a one-year horizon it amounts to 292 360 082 DZD or 0.367% of the bank's total exposure on this portfolio.

The expected loss is a very important measure for the bank's decision-makers because it allows them to better manage its provisioning policy. Indeed, the prior estimation of the expected Loss gives the bank the advantage of provisioning receivables ex ante ante instead of doing it ex post as it is the case today for all the Algerian banks.

Algerian banks provision their receivables according to the different classes of risks dictated by the by the Bank of Algeria.

However, the expected loss is not obviously the loss that will actually be realized. In practice, the actual losses have practically no chance of being identical to this average loss; they take on higher or lower values.

B. The Value At Risk

The Value at Risk (VaR) is defined as the maximum loss that can be incurred on a credit (or a credit portfolio) at a given time horizon and confidence level.

It is equal to the quantile of order α of the loss density function (PDF). It can also be obtained by summing the expected loss and the unexpected loss.

As discussed earlier, the actual losses may well exceed the expected losses, which is why the bank is just as concerned about the level of unexpected losses as much as the level of expected losses. These losses, because of their unpredictable nature, cannot be known in advance. Therefore, we are particularly interested in a time horizon and a certain percentage of chance, to determine the maximum potential amount that these potential amount that these losses can reach.

The confidence level recommended by the Basel Committee is 99.9% and the confidence horizon is one year. This recommendation aims to ensure a maximum level of security. Thus, the VaR has only a 0.1% chance of being exceeded.

In the case of our portfolio, with a one-year horizon and a confidence level of 99.9%, the VaR is equal to 1 631 215 874 DZD or 2.05% of the total exposure of the bank, which means that we are 99.9% sure that the amount losses on our portfolio will not exceed the amount of 1 631 215 874 DZD.

However, taking a considerably higher confidence level is more conservative, but it is restrictive because it requires a considerable amount of capital.

As with economic capital, the Value at Risk increases exponentially with increasing confidence. exponentially with increasing confidence. However, the 50% VaR at a one-year horizon VaR at a one-year horizon, which is also the median of the PDF, is special in that it is the average loss, which means that it is likely to incur an overall loss that is less than the expected less than the expected loss.

On the other hand, it is also possible to calculate the contribution to VaR (RC) in order to detect the main sources of risk on our portfolio. This is an indicative element which can be very useful for the bank's decision makers as economic capital is a very expensive source for the bank.

4.3.3. Expected Loss and Risk Contribution :

The Expected Loss (EL) and the Risk Contribution (RC) are given by the model for each security and in an automatic way,

It only remains to calculate the unexpected losses at the individual level by the following formula :

$$\mathrm{UL_i} = RC_i - \mathrm{EL_i}$$

Table 26: Calculating unexpected losses (Extract)

Name	EL	RC	UL
1	74,041,998	337,724,191	263,682,194
2	104	32,108	32,004
3	1,070,883	1,758,387	687,504
4	23,843,091	232,051,192	208,208,101
5	2,056,342	4,467,838	2,411,496
6	2,343,678	4,742,148	2,398,470
7	2,247,486	4,369,365	2,121,879

4.4.Stress Tests

The stress tests are carried out with the aim of identifying the impact of an economic downturn leading to a recession in the economy or in a given sector.

In order to achieve this, we will proceed to a rating downgrade for all borrowers affected by the same sector. We repeat the operation for all the sectors in order to deduce from their behavior in unfavorable situations those who should benefit from of intensified monitoring by the bank.

4.4.1. Sectorial Stress-test

The simulation will be done by downgrading the rating of a given sector by lowering the rating of each company which belongs to that sector to this sector all at once.

We chose the constrcution sector, since as we've already seen, it represents more than 28% of the bank's total portfolio exposure , in addition to this, it is the sector that was most affected by the worlwide Covid-19 pandemic. Which massively stalled the transport of marchandise both locally and internationally, and stalled most ongoing construction projects.

After modeling with simulated data, we had the following results :

Table 27: VaR before and after Construction Stress-test

Percentile	VaR	VaR(Stress-test)	Variation
Mean	292,360,082	506,730,603	73.32%
50	242,107,232	353,362,480	45.95%
75	420,309,509	769,459,434	83.07%
95	807,578,566	1,427,251,011	76.73%
98	974,823,596	1,680,958,827	72.44%
99	1,164,041,678	1,975,006,436	69.67%
99.5	1,298,226,557	2,237,999,764	72.39%
99.8	1,448,096,239	2,461,790,632	70.00%
99.9	1,631,215,874	2,741,728,309	68.08%

We notice that the change in the Value at Risk is considerably higher for all confidence levels. For an α=99.9%, the VaR increases with a rather large amount 1 110 512 435 DZD , i.e. a variation of 68.08%, the bank will revise its economic capital upwards as well.

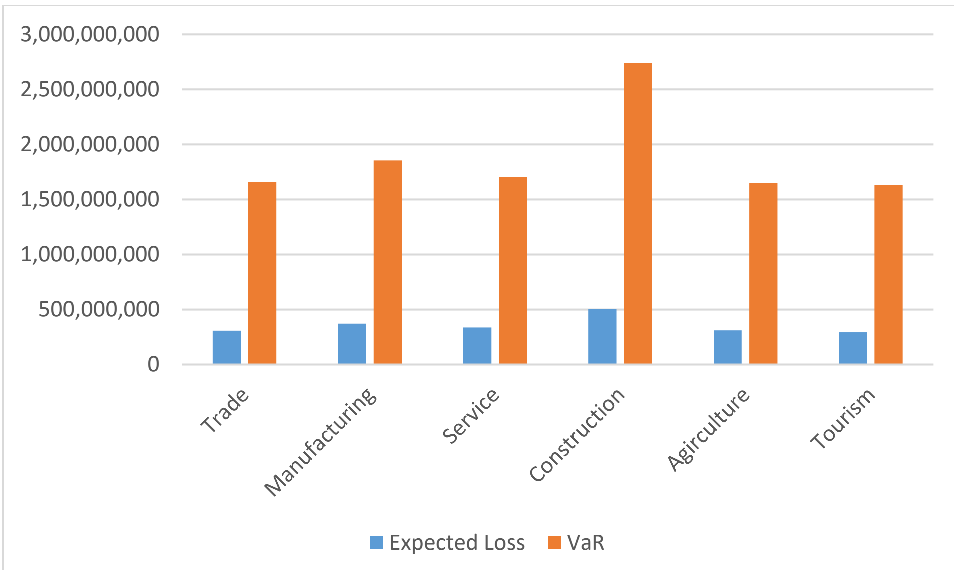
The expected loss is estimated at 506 730 603 DZD, while the unexpected loss sits at 2 234 997 706 DZD

We will now downgrade the rating for the other major sectors in our portfolio, each one separately, to compare the impacts caused by each sector on our overall portfolio.

Table 28: Effect on portfolio VaR and Expected Loss of Stress-testing each sector

	Trade	Manufacturing	Service	Construction	Agriculture	Tourism
Expected Loss	308,020,944	370,912,519	337,027,283	506,730,603	309,692,554	292,563,817
VaR	1,657,476,919	1,854,433,619	1,705,220,480	2,741,728,309	1,650,883,533	1,631,564,429

Figure 27: Effect on portfolio VaR and Expected Loss of Stress-testing each sector



As expected, we note that it is the deterioration of the construction and public works sector that has the greatest impact on the portfolio's losses, followed by the manufacturing and service sectors.

These three sectors therefore require the largest endowments in economic capital.

This significant impact on portfolio losses is explained mainly by :

They constitute a significant share of exposure in the portfolio, 28% for the construction sector, 21% for manufacturing and 20% for services.

The impact of the deterioration of the construction and public works sector is the most important because the number of companies affected is quite high. 71 companies in the entire portfolio, 14 of which will have a very high level of risk (B or lower).

4.4.2. Global Stress-test:

Now we simulate the worst-case scenario that predicts a general deterioration of the economy. So, we will downgrade all the borrowers of at the same time, in this way we will act on the average default rates.

The following table compares the maximum losses calculated previously for the base sample and those calculated after the ratings downgrade:

Table 29: VaR before and after global Stress-test

Percentile	VaR	VaR(Stress-test)	Variation
Mean	292,360,082	663,147,310	126.83%
50	242,107,232	530,960,073	119.31%
75	420,309,509	925,823,614	120.27%
95	807,578,566	1,614,856,401	99.96%
98	974,823,596	1,877,848,130	92.63%
99	1,164,041,678	2,214,410,540	90.23%
99.5	1,298,226,557	2,465,398,998	89.91%
99.8	1,448,096,239	2,701,797,180	86.58%
99.9	1,631,215,874	3,015,482,141	84.86%

This scenario has a worrying effect on the bank's solvency, as the Value at Risk at a horizon of one year have almost doubled for all confidence levels. The VaR at 99.9% had an increase of 1 358 005 222 DZD or 84.86% increase.

The average new loss is equal to 663 147 310 DZD, which means the unexpected losses is equal to 2 352 334 831 DZD,

After these simulations, the conclusion to be drawn is that the bank must review its policy of distribution policy, so it should not expose itself further to the fragile sectors, particularly that of construction and public works.

Chapter conclusion

This chapter was devoted to the modeling of the credit risk with the aim of estimating its main measures of credit risk. At the beginning, we started with a brief presentation of the presentation of the Algerian Bank of Local Development which is the banking establishement where our Internship took place, then a descriptive study of our sample was necessary to draw the essential characteristics of our portfolio. Then, we defined the parameters we need for the modeling (Default rate, LGD, EAD…) where we encountered some difficulties related to a lack of data that we have dealt with to the best of our ability. Lastly, we carried out the modeling and we got results that the bank can use in the framework of the management of its credit portfolio. Thus, preventing the risk of the bank’s insolvency.

It should be noted that our work has been developed in a pedagogical framework to illustrate how a risk model can be integrated into the management of a bank. In no way, do we claim that this study can be integrated into the bank's internal credit risk management policy, because to be able to reach such large-scale objectives, in-depth studies and much more human and material ressources must be implemented.

Conclusion

Currently, most Algerian banks are still at the stage of identification of banking risks. To be able to speak about measurement and management of these risks, the central bank is gradually introducing the Basel II provisions and to encouraging the development of internal models. The Basel Committee has proposed for banks in countries that are not part of the G-10 (notably Algeria) and that want to implement the Basel II dispositions, to take into account the local context. In this regard, banks must make a continuous effort to put in place systems that meet international standards. This effort must be directed towards improving their predictive power through quality of ratings, a greater diversity of data collected and a greater control of models.

In that context the BDL is currently working on developing and implemeting its own internal rating system, which will facilitate the study and evaluation and of a bank credit application, thus greatly helping the bank manage its credit risk.

Our work aims to show the importance of credit risk models for banks.First, we have discussed the theoretical notions on credit risk and its management and we reviewed the international prudential standards and the adaptation of the Algerian case to these standards. Then we presented the different ways and mechanisms through which the credit risk can be managed and measured. Finally, we proceeded to the application of the CreditRisk+ model to a sample of loans from the Bank of Local Development in order to derive the main measures, mainly the Value at Risk. The exploitation of the results of this modeling has allowed to show the contribution of this model in particular in terms of decision making. Indeed, these results allow a better management of the portfolio and help in the construction of a short and medium term credit policy.

At the end of this work, it appears that the Value at Risk at the 99.9% confidence level attached to the portfolio of loans granted by BDL to companies amounts to 1 631 215 874 DZD;

In addition, the expected loss on this portfolio, which is covered by the mechanism of margins and provisions, amounts to 292 360 082 DZD

From the above, we can finally deduce by simple difference (Value at Risk minus the expected loss) the unexpected loss attached to this portfolio and which amounts to 1 338 855 792 DZD; that is to say approximately 1.7% of the total receivables of the considered portfolio.

However, this work was still limited by time and quantity of data collected. Indeed, such a setup will allow the development of a more robust model with a continuous work by a team of credit risk management specialists and over a longer time horizon.

Nevertheless, during our internship and in the course of this work, we had some remarks, since credit risk management constitutes a priority for the BDL, which is currently taking big steps in this direction by working on the implementation of a rating system for borrowers. However,since we believe this remains insufficient, we have tried to formulate some recommendations that we we consider necessary:

-Improve the information and database management system to facilitate the access of the available client data and take advantage of it.

-Accelerate the implementation of the borrower rating system by conducting more in-depth studies of the bank's empirical data and generalizing it to all of the bank's borrowers.

-Allow the system to have other outputs besides ratings, such as default probabilities, which are essential for measuring credit risk.

-Investigate the bank's recovery policy and identify all aspects of the bank's potential loss in the event of counterparty defaults.

Finally, we can say that the management of the credit portfolio is a relatively recent discipline, at least for Algerian banks. It is developing and is beginning to be taken into consideration in recent years.

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