Department of Accounting and Finance

MSc. Accounting Taxation and Financial Management

Master Thesis

"Credit Risk Modeling Under the IRB Approach "

Of

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Contents

Abstract

Over the past few years, there has been a significant shift in how commercial banks evaluate business lending. A bank's credit specialists' subjective judgments have given way to increasingly objective statistical models in recent years. Banks are beginning to see the massive importance of accurate credit risk forecasting. The economic downturn of 2008 will almost certainly increase demand for reliable modeling techniques. The credit assessment modeling framework is developed in this thesis. After attempting a variety of model-building strategies, we conclude that logistic regression provides the most promising foundation for future credit rating models. The complementary log-log link was assumed to be most suited for modeling the default event after an evaluation of the performance of various link functions for the logistic regression.

There is no one metric that can be used to determine whether a credit rating model has been successfully validated. To address this issue, we propose use principal component representations of low-dimensional measures of discriminating power. Having a single metric by which to judge a model's efficacy makes developing new ones a considerably more time- and labor-efficient procedure. Selecting variables is the same way. When compared to what would be available at most financial institutions, the data employed in the modeling process is sparse. We offer a resampling procedure that might help when working with a small dataset and need reliable performance estimates from your model.

1. Introduction.

Banking is built on the idea of profiting by loaning money to ones that are in need of money. Commercial banks are often substantial in size, and their core business model continues to be based on financial intermediaries through (l) deposit taking, wholesale funding (e.g. corporate bonds and covered bonds), and shareholder capital, and (2) lending, which is a key source of credit risk. Loans for homes, businesses, and other small and medium-sized enterprises (SME) comprise the majority of banking institutions' loan portfolios. The owners of small and medium-sized enterprises (SMEs) frequently use real estate as collateral for small business loans. Lending portfolios of commercial banks are heavily weighted toward the property market. Auto loans, credit card loans, and student loans are all types of consumer loans, and there's also a separate category for business loans. Loans to major corporations exist, although they face competition from alternative capital market funding methods (such as the sale of stock and bonds). Consider the fact that there are several mortgage options to choose from. Loan types include prime mortgages, subprime mortgages, reverse mortgages, home equity loans, HELOCs, interest-only loans, variable-rate loans, fixed-rate loans, and hybrid loans. Credit risk also arises through securitization investments, contingent credit exposures (loan obligations and guarantees), credit derivatives, and over-the-counter (OTC) derivatives, in addition to traditional fixed income securities (such as bank, corporate, and government bonds).

Once a borrower starts making payments to a bank to repay a loan, the bank will start collecting interest on the amount borrowed plus the amount paid back. Because it's possible that some loan-seekers won't pay back their debts, the bank suffers a loss when this happens.

Financial institutions determine if an applicant is creditworthy throughout the loan application procedure. Borrowers' creditworthiness is determined in part by how likely they are to repay their loans on time. In finance, credit risk refers to the possibility that a borrower's creditworthiness may turn out to be overestimated. There is a lot of recent progress being made in the area of credit risk modeling. Credit risk on corporate loan was formerly determined by the subjective examination of credit specialists at financial institutions before the seminal work of Altman (Altman, n.d.).

When reporting to both internal and external stakeholders, the probability of default is a crucial metric for any credit institution.

Bank credit risk evaluations are typically referred to as credit rating models which play an integral role in the day-to-day activities of every credit institution.

1.1 Shift In Credit.

After the Great Financial Crisis that occurred from 2007 to 2009 Prudential authorities have tightened up their criteria for risk models in the wake of the 2008 financial crisis, and strict regulations are being rolled out throughout the world such as:

- Adoption of Basel II[1]: Capital amplification, leverage and liquidity ratios, liquidity analysis, and impact assessment are all aspects of banking covered by the Basel guidelines.

- Each risk model must undergo yearly stress testing as mandated by regulators.

- Authorities are now examining areas where regulation is applied inconsistently with the goal of ensuring uniformity across financial institutions and products. Revitalization of the securities market: The private (i.e., non-government-supported) securitization market in particular has experienced a fall in volume, while this is true of many other markets as well.

- More data is gathered and made available to credit risk assessors thanks to centralized transaction repositories and the tracking of individual loans.

- Accurate credit risk monitoring is essential to boosting banking efficiency, competitiveness, deregulation, and simplicity.

There have been several developments in the methodology of risk models in recent years. The scientific method was heavily utilized, with studies frequently abstracting from economic cycles and often being carried out in lab settings to assure repeatability. Modern credit risk models are empirical and use past data, which includes information on major recessions like the Great Financial Crisis.

The economic underpinnings of the processes that generate data are factored into cutting-edge credit risk models. Consider the typical practice of accounting for the full cycle of a financial instrument, from inception through payout, default, or maturity, all while keeping an eye on the economy. Bayesian modeling, nonparametric modeling, and frailty modeling all fall under the category of efficient analysis of accessible data. Models of risk are refined to better utilize both observable and non-observable data.

[1] More information on the Basel regulations will be provided later.

A word of caution is warranted notwithstanding all these developments. To this day, we still use assumptions and look back at observed data to create our empirical risk models, so there is always some degree of model risk involved. The R-squared values of 20% for linear LGD and exposure at default (EAD) models are relatively typical, for instance. This literature suggests that there is a sizable amount of variation that these models do not explain, as R-squared represents the percentage of the variability that is explained by the model. For the foreseeable future, we will be very busy improving our models.

1.2 of Credit Concepts

Regulatory and Economic Capital

There are several ways in which money might enter a bank. Money deposited in various bank accounts (checking, savings, term, etc.) is the primary source. The depositors are compensated with a periodic interest rate that might be either fixed or variable. In addition, the bank can receive funding from investors and shareholders who have purchased shares. A dividend is a distribution of a portion of a company's earnings to its stockholders. A bank relies on depositors' funds and shareholder investment.

In terms of the bank's assets, the funds are invested in various financial instruments.

Lending is a fundamental aspect of a bank's operations and represents an initial investment. Obligors can get loans from financial institutions for a variety of reasons, including making large purchases like homes and cars, furthering their education, and taking extended vacations. Stocks and bonds are only two examples of market assets that might be invested in.

Keep in mind that there is always a degree of danger involved with these investments. There is always the risk that the debtor won't pay back the loan, or that the market will crash, reducing the value of the securities they're backed by. Given the importance of banks to any economy, they must be adequately safeguarded against the hazards to which they are exposed. The risk that banks assume on their asset side should be paid for by suitable liabilities to protect their depositors, and bank insolvency or collapse should be avoided at all costs. These individuals should have unwavering access to their savings funds at any time they request a return of their principal. Accordingly, a bank needs adequate shareholder capital as a safety net in case of losses. Equity or capital in fact might comprise retained earnings and reserves. Therefore, a well-capitalized bank has adequate equity to cover its risks. As a result, there has to be a one-to-one correspondence between danger and reward in terms of equality.

This connection is typically measured in two stages. A risk number is first used to quantify the asset side risk. The method then uses this value to determine the exact amount of equity and capital that will be needed. The formula for calculating this risk number and how it should be calculated are also contested.

The first perspective is a regulatory one, which emphasizes the establishment of rules for determining the appropriate formula and methodology for arriving at the risk number. Consequently, the required amount of capital that a bank must maintain in accordance with a rule is known as regulatory capital. However, even without rules, banks would know that they need to maintain a certain level of equity capital in order to be safe. In this scenario, the risk number and the buffer capital would be determined using the respective parties' internal risk modeling processes and procedures. Thus, we arrive at the idea of economic capital, which is the total quantity of money a bank has according to its own internal modeling plan and policy. The higher of the economic capital and the regulatory capital is what we call the bank's "actual capital." For illustration's sake, Bank of America states that its end-of-2015 ratio of total capital to risk-weighted assets utilizing advanced methodologies was 13.2 percent, whereas the present regulatory minimum capital is 8 percent (this number will climb once Basel Ill is completely phased in). This means the current capital buffer is 5.2%.

It's important to remember that different forms of capital exist for different purposes. Shares of ordinary stock, preferred shares, and retained earnings are the standard components of Tier I capital. Tier 2 capital consists of lower quality assets such as subordinated loans, revaluation reserves, undisclosed reserves, and general provisions.

Tier 3 capital, which consists of short-term subordinated debt, was also a part of the Basel I Capital Accord, but it was removed in the more recent Basel Ill Capital Accord, as we shall see in the next section.

2.BASEL

2.1 Introduction

Examining the Basel, I, Basel II, and Basel III Capital Accords in further detail. These rules were put in place so that banks would have a better idea of how much money to set aside as a safety net in case of a variety of potential disasters. Credit risk is a major concern, therefore here we'll look at how these agreements have affected the evolution of PD, LGD, and EAD credit risk models. Many parts of credit risk analytics are founded on the Basel laws; we shall return to the various difficulties in subsequent chapters.

2.2 Basel I

As a means of enhancing banking regulation, the Basel Committee on Banking Supervision proposed the Basel Accords. As early as 1974, the G10 central banks established this group. There are now 27 members. The meetings take place on a regular basis at the Bank for International Settlements (BIS) in Basel, Switzerland.

In 1988, the Basel I Capital Accord was established as the first such agreement. The purpose of establishing regulatory minimum capital requirements to guarantee banks' ability to repay depositors' money at all times has previously been established. The Basel I Accord established the concept of the capital or Cooke ratio, which is the ratio between the available buffer capital and the risk-weighted assets, with a primary emphasis on credit risk. In other words, the capital must be more than 8% of the risk-weighted assets, the minimum threshold imposed by the regulation. We have been asked where we got this figure, and our best guess is that it was a standard in the industry when the first Basel Accord was put into effect. Changing the capital requirement, even by a few percentage points, is a difficult and time-consuming endeavor for major banks. It was previously established that Tier I and Tier 2 capital may both contribute to the total.

Credit risk was given its own set of fixed risk weights in the Basel I Capital Accord. A risk weight of 0 percent was assigned to cash exposures, 50 percent to mortgages, and 100 percent to all other commercial exposures. Let's say you're looking at getting a mortgage for $100. With a risk weight of 50% applied, RWA is now $50. The probability we were discussing previously is this one. Using the concept that regulatory minimum capital is 8% of risk-weighted assets, we may derive the necessary capital. As a result, we have a $4 minimum funding need. For our mortgage of $100, we need at least $4,000 in equity to account for any credit losses.

The Basel I Accord was a positive development in the direction of enhanced risk management, but it was not without significant flaws. For starters, the risk weights only considered the exposure class and not the obligor or product attributes, which meant that the solvency of the debtor was not appropriately considered. Credit risk was not adequately reduced due to adequate recognition of collateral guarantees. It also presented several possibilities for regulatory arbitrage, the practice of exploiting regulatory gaps to the greatest possible extent in order to save money. In the end, it took into account just credit risk and not operational or market risk.

2.3 Basel II

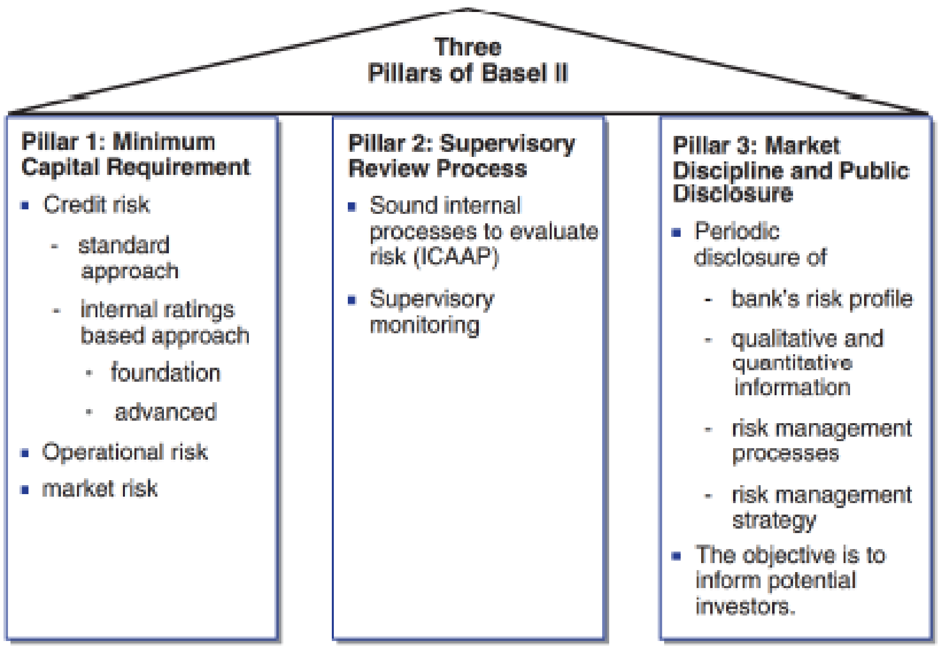
The Basel II Capital Accord was put in place to make up for the deficiencies of the earlier Basel I Capital Accord. There are three main components: Pillar I, which addresses the required level of capital, Pillar II, which details the mechanism by which supervisory review is conducted, and Pillar III, which addresses market discipline and transparency. (Please refer to Figure 1 & Figure 2)

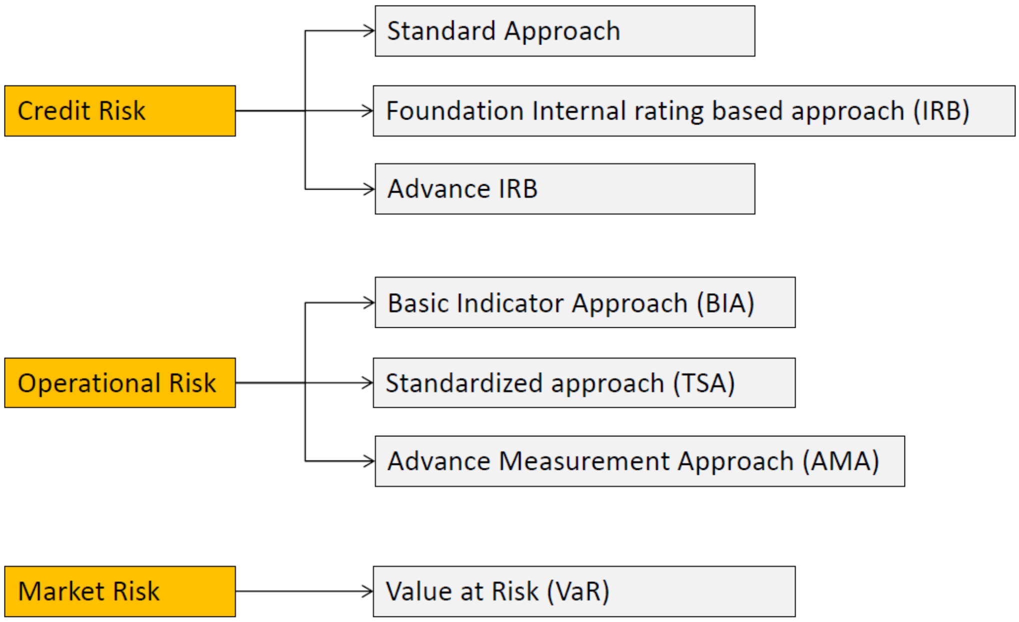
There are three distinct categories of risk covered by Pillar I. Loaning money to obligors carries with it the danger of losing that money. An organization faces operational risk whenever there is a potential for a financial loss as a consequence of insufficient or failing internal processes, people, and systems, or external events. Common causes of this type of loss include dishonesty, destruction of physical assets, and malfunctioning technology. Banks that deal in cash or derivative goods are exposed to market risk, or the danger of losing money as a result of favorable changes in the market. Stock market risk, foreign exchange risk, commodities risk, and interest rate risk are all instances that come to mind. The concept of credit risk is dissected in great detail throughout this book. Credit risk can be modeled using one of three methods, all of which are anticipated by the Basel Il Capital Accord: the basic approach, the foundation internal ratings-based approach, and the advanced internal ratings-based approach. Making quantitative models for gauging credit risk is what it comes down to. (Supervision., 2006)

There must be an audit of all quantitative models developed under Pillar I. This is addressed in detail in Pillar 2. Implementing reliable methods for assessing risk, such the internal capital adequacy assessment process (ICAAP), and supervising their implementation are crucial steps.

All quantitative risk models must be cleared before they can be released to the market. The third pillar addresses this issue. Here, a financial institution will give the market regular updates on its risk profile and qualitative and quantitative data on its risk management procedures and plans. By informing and persuading investors of the bank's strong risk management plan, the institution might perhaps attract money at more favorable interest rates.

Figure 1:Basel II pillars





2.4 Basel III

When the financial crisis broke out with the fall of Lehman Brothers in 2008, it revealed the banking industry's reckless lending practices and the absence of sufficient liquidity buffers to weather the storm. Inadequate governance and risk management processes resulted in unsustainable credit expansion, which in turn led to excessive leverage.

During the financial crisis, flaws in the “Basel Committee on Banking Supervision” hereafter BCBS's handling of complicated securitization holdings, off-balance-sheet entities, and trading book exposures became apparent. In 2010, the BCBS published two documents establishing the requirements of Basel Ill, which had been endorsed by the G20 Leaders' Summit in Seoul (Supervision, 2011) (Supervision., 2013)
The Basel II framework updated and fortified the three foundations established in Basel I. And it imposed several additional liquidity and capital demands:

- The capital conservation buffer (CCB) is an extra capital requirement that serves as a safety net for the present minimum necessary capital. When this safety cushion is threatened, dividend distributions are reduced to speed up the building of the bare minimum of capital.
- The countercyclical capital buffer, which is supplementary to the minimum required capital, limits banks' participation in system-wide credit growth and aims to reduce their losses in credit downturns; If this additional buffer requirement begins to erode, payouts of earnings will be restricted, enhancing the accumulation of the minimum required capital.

- Increased provisions for international supervision and resolution are included in the capital surcharge for globally systemically important banks (G-SlBs). This capital fee for G-SlBs is complemented by stricter regulations for international banking oversight and resolution.
- The LR is a ratio of a bank's total on- and off-balance-sheet liabilities to the minimum required level of loss-absorbing capital (T1 capital). The non-risk-weighted total assets reported in a bank's financial statements are similar to the concept of total bank exposures used to calculate LR.
- Minimum requirements for cash available or other highly liquid assets to cover 30-days of operating expenses in the event of a financing shortfall are established by the liquidity coverage ratio (LCR)
- The NSFR, or net stable funding ratio, is a longer-term ratio used to track maturity mismatches throughout the whole balance sheet.

For Basel Ill to be fully implemented, the following minimal resources would be needed:

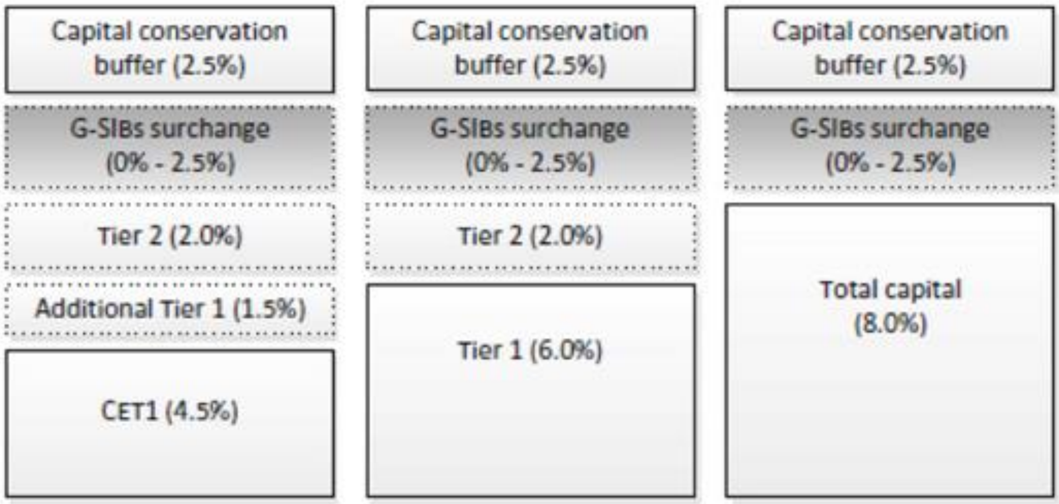
With the T1 at 6.0% as of January 2015 and the CET l at 4.5%, this means that the extra Tl capital should comprise no more than I of the total RWAs. Compared to Basel I, the minimum TC requirement wouldn't alter and would stay at 8.0%. T2 capital would make up no more than 2.0% of RWA if the minimal TC requirement were met. Capital surcharges of up to 3.5 percent apply to G-SlBs as of 1 January 2016.

The LR total exposure measure's minimum capital requirement under Pillar l has changed to Tl as of I January 2018. The best way to adjust this prerequisite is currently being discussed.

In 2019, the CCB will be 2.5% of RWA. The CCB will contain CET1 and be an add-on to the 4.5% CET1 minimum needed capital, whereas in 2018, the NSFR will be 100%.

The LCR will be set at 100% as of January 1, 2019. The liquidity coverage ratio (LCR) will be established at 100%, meaning that the company has a large enough amount of high-quality liquid assets to cover the cash outflows that would occur in a severe but short-term stress situation. Figure 2 is a visual representation of the required starting capital.

Figure 2:Basel III minimum Pillar 1 risk-based capital requirements



2.5 Basel Approaches to credit Risk Modeling

Credit risk modeling considering the Basel Capital Accords will be discussed below. Standardized, foundational, and advanced internal ratings based techniques have been considered; these are the three main options. The methods vary in how sophisticated they are and how much leeway they provide you when it comes to applying your own estimates of risk.

2.5.1 Standardized Approach

First, we will go through the conventional method. In this method, credit ratings for non-retail risks are provided by independent ECAIs (External credit assessment institutions). Standard & Poor's, Moody's, and Fitch are well-known ECAIs. The Basel Accords have established eligibility requirements for ECAI status, including objectivity, independence, openness, and disclosure, in light of the significant influence of ECAls. The ECAIs' ratings will subsequently be applied to the risk weights specified in the agreements. Risk weights may include various exposures, including those to sovereigns, banks, corporations, and others. The actual capital is determined by assigning a value of 8% to the risk-weighted assets.

The retail industry uses a risk weight of 75% for non-mortgage risks and 35% for mortgage exposures. You may recall that the risk weight for mortgages was 50% greater in Basel I. In the business world, risk weights range from 20% for AAA-rated risks to 150% for exposures rated D or lower. The risk weights for sovereign debt range from zero percent for AAA-rated countries to one hundred fifty percent for countries rated B or worse. The risk weight may increase to 150% for defaulted loans. Please be aware that the European Banking Authority (EBA) has implemented mapping methods to convert FCAIS credit ratings to credit quality steps, which can then be mapped to risk weights using the European capital directive.

2.5.1.1 An example of the Standardized Approach

Let's pretend our company has a $1,000,000 unsecured exposure that has a 5 year maturity and an AA grade from Standard & Poor's. Making use of the European regulation. A credit quality step of l, as represented by an AA rating, will translate to a risk weight of 20% as per Article 122. This makes the risk-weighted assets 20% of S1,000,000, or S0.2,000,000. The required amount of capital to operate within the law is then 8% of that amount, or $50.016 million. When it comes to collateralized loans, the standardized method also offers credit risk reduction facilities.

The usual approach may appear straightforward and attractive at first glance, but it has problems, including discrepancies in the ratings of various FCAIs and the risk that banks will cherry-pick the ECAls. There are also issues with the extent to which they protect against different hazards. For instance, the main distinction between retail exposures is whether or not they involve a mortgage. It would be ideal to have a more nuanced system of classification. A comprehensive risk profile for each obligor that takes into account not just default risk but also loss and exposure risk via LGD and EAD is ideal.

2.5.2 Internal Ratings Based(IRB) approach

The Internal Ratings Based Approach (IRB) is a methodology used by banks to assess credit risk and determine the amount of regulatory capital required to cover that risk. It is a framework established by the Basel Committee on Banking Supervision (BCBS) as part of the Basel II and Basel III frameworks.

Under the IRB approach, banks are allowed to use their own internal models and data to estimate the

- PD is stressed via the concept of a worst-case default rate given a virtual macroeconomic shock based on a confidence level 01 99.9 percent and a sensitivity to the macroeconomy that is based on the asset correlation.
- LGD is based on an economic downturn.
- EAD is based on an economic downturn.

This allows banks to have more flexibility and potentially more accurate risk assessments compared to the standardized approach.

There are two types of IRB approaches:

Foundation IRB (F-IRB): Banks using the F-IRB approach must rely on some standardized inputs, such as external credit ratings, to determine credit risk. They can then use their internal models to estimate other credit risk parameters.

Advanced IRB (A-IRB): Banks using the A-IRB approach have more flexibility and can rely solely on their own internal models to estimate all credit risk parameters. However, to qualify for the A-IRB approach, banks need to meet specific regulatory requirements, including having robust risk management systems and data infrastructure.

Figure 3 F-IRB and A-IRB differences

	PD	LGD	EAD	Asset Correlations
Foundation approach	Internal estimate	Regulator's estimate	Regulator's estimate	Regulator's estimate
Advanced approach	Internal estimate	Internal estimate	Internal estimate	Regulator's estimate

The IRB approach allows banks to differentiate the risk profile of individual borrowers, taking into account factors such as financial strength, industry characteristics, and historical default rates. By using their own models, banks can tailor their risk assessments and determine appropriate capital requirements more accurately. However, this approach also requires banks to have sophisticated risk management systems, data collection processes, and ongoing validation procedures to ensure the accuracy and integrity of their models.

It's worth noting that the IRB approach is subject to regulatory oversight, and banks are required to undergo periodic reviews and validations of their models by regulatory authorities to ensure compliance and sound risk management practices.

2.5.1.1 An example of the Internal Ratings

Based (IRB) approach for credit risk assessment using the Foundation IRB (F-IRB) method. In this case, banks utilize external credit ratings as a starting point and then apply their internal models to estimate other credit risk parameters.

Let's assume we have a bank assessing the credit risk of a corporate borrower. The bank assigns an external credit rating of "AA" to the borrower. Here are the steps involved in the F-IRB approach:

Probability of Default (PD):

The bank will use its internal model to estimate the probability that the borrower will default within a given time frame. Let's say the bank's model estimates a PD of 3% for this borrower.

Loss Given Default (LGD):

The bank needs to determine the potential loss in the event of default. LGD represents the proportion of exposure that the bank expects to lose if default occurs. Let's assume the bank's model estimates an LGD of 50% for this borrower.

Exposure at Default (EAD):

EAD represents the exposure amount at the time of default. It reflects the total amount the bank expects to be at risk if the borrower defaults. Let's assume the bank's internal model estimates an EAD of $10,000,000 for this borrower.

Capital Requirement:

To calculate the capital requirement, we multiply the PD, LGD, and EAD. The capital requirement represents the amount of regulatory capital that the bank needs to set aside to cover potential losses due to credit risk. Using the values mentioned above:

$$\text{Capital Requirement} = PD \times LGD \times EAD$$

$$= 0.03 \times 0.5 \times \$10{,}000{,}000$$

$$= \$150{,}000$$

So, in this example, the bank would need to hold $150,000 of regulatory capital to cover the credit risk associated with this borrower.

It's important to note that the mathematical expressions and calculations involved in the Advanced IRB (A-IRB) approach can be more complex, as banks use their own models to estimate all credit risk parameters without relying on external credit ratings. The A-IRB approach involves more sophisticated statistical techniques and data analysis methods to assess credit risk accurately.

3. Credit scoring

It is a widely used method for assessing the creditworthiness of individuals and entities. It involves evaluating various factors to assign a numerical score that indicates the likelihood of a borrower defaulting on their financial obligations. Credit scoring helps lenders make informed decisions regarding loan approvals, interest rates, and credit limits. There are two main approaches to credit scoring: the judgmental approach and the statistical approach.

3.1 Basic Approaches

3.1.1 Judgmental Approach

The credit scoring methodology that employs a judgmental approach entails the utilization of specialized expertise and subjective evaluation to determine the creditworthiness of an individual. This methodology involves the utilization of the knowledge, proficiency, and perception of credit officers or underwriters to arrive at credit determinations. These experts assess the creditworthiness of a potential borrower by considering various factors, including but not limited to their payment history, employment tenure, income bracket, and personal recommendations. They allocate subjective evaluations or grades according to their evaluation. The evaluative technique of being judgmental can prove to be advantageous in assessing borrowers who possess a restricted credit history or in situations where there is a dearth of data to base decisions upon. Nonetheless, the method is susceptible to partiality and subjectiveness, leading to irregular verdicts (L.C. Thomas, 2002) (Van Gestel, 2009).

Advantages of the Judgmental Approach:

- Flexibility: The judgmental method provides for a flexible evaluation of creditworthiness, taking into account unique conditions and elements that statistical models might not be able to account for.

- Contextual Understanding: Credit officers can use their knowledge of complicated circumstances to comprehend them and evaluate credit risk based on contextual and qualitative data.
- Quick Decisions: Judgments can be made thanks to the judging method, particularly when past credit data may not be readily available.

Limitations of the Judgmental Approach:

- Subjectivity and Bias: Because various credit officers may have diverse perspectives and interpretations, the judgmental method may inject biases into credit judgments.
- Lack of Consistency: The judgmental method might result in uneven credit determinations due to the absence of uniform standards and scoring systems.
- Limited Scalability: Because it mainly relies on individual experience and manual assessment, the judging technique could not be scalable for high quantities of loan applications.

3.1.2 Statistical Approach:

The credit scoring methodology that employs statistical techniques relies on empirical examination and impartial models. The methodology employed involves utilizing past credit information to formulate mathematical models that forecast the likelihood of credit default. This methodology is predicated on the supposition that prior credit conduct serves as a reliable predictor of future conduct. Statistical models take into account a variety of factors, such as payment history, credit utilization, credit history duration, credit account types, and public records. Through the examination of extensive data sets, statistical models are capable of detecting patterns and correlations in order to make estimations regarding credit risk. Logistic regression is the prevalent statistical model employed in credit scoring.

Advantages of the Statistical Approach:

- The utilization of statistical models offers objectivity and consistency in evaluations due to their reliance on mathematical computations and predetermined standards.
- The efficient processing of large volumes of credit data is facilitated by statistical models, resulting in improved scalability and more precise predictions.

- The integration of various credit factors in statistical models enables the identification of their respective significance in forecasting credit risk.

Limitations of the Statistical Approach:

- Statistical models place significant reliance on historical credit data, assuming that previous credit behavior will be replicated. The aforementioned measures may not comprehensively encompass unique personal circumstances or unanticipated occurrences.
- One of the limitations of statistical models is their potential inability to fully comprehend the contextual nuances of a borrower's creditworthiness, as they tend to prioritize quantitative information.
- The development and upkeep of statistical models necessitates proficiency in data analysis, model creation, and continuous monitoring.

3.2 Logistic Regression:

Logistic regression is a statistical methodology employed to establish a model that describes the association between a dependent variable, namely credit risk, and one or more independent variables, which are credit-related factors (B. Baesens, 2005). The estimation of the likelihood of an event, such as default or delinquency, is predicated upon the independent variables. The logistic regression model assigns coefficients or weights to each independent variable, which signify its influence on the credit risk. The aforementioned coefficients are integrated with the borrower's information in order to compute a credit score. Credit scoring can also utilize various statistical techniques, such as decision trees, neural networks, and ensemble models.

The linear probability model uses economic and financial data to estimate the probability of default (PD). In this model we running a linear regression in which the explained variable, D, can have a value of 1, in the case of default, or a value of 0, when the firm is paying its debts.

The explanatory variables can be any risk metrics that reflect the firm's financial strength, such as the financial leverage ratios, liquidity ratios or profitability ratios. The model is estimated for many firms using a linear regression from the form:

$$D_i = b_i x_{ij} + \varepsilon$$

Where:

x_{ij}— The explanatory variables (financial ratios) of firm i;

b_i— A coefficient that measures the importance of a variable in explaining default

Upon receipt of the coefficients from the regression run one can multiply them by the firm's explanatory variables in order to get the firm's probability of default

An expanded form of the above could be

$$D_i = b_0 + b_2Age + b_2Income + \ b_3Employed \ + \varepsilon$$

However when estimating this using ordinary least squares (OLS) two key problems arise
1. The errors/target are not normally distributed but follow a Bernoulli distribution with only two outcomes.
2. There is no guarantee that the target is between 0 and 1; it would be handy if it were, because then it could be interpreted as probability.

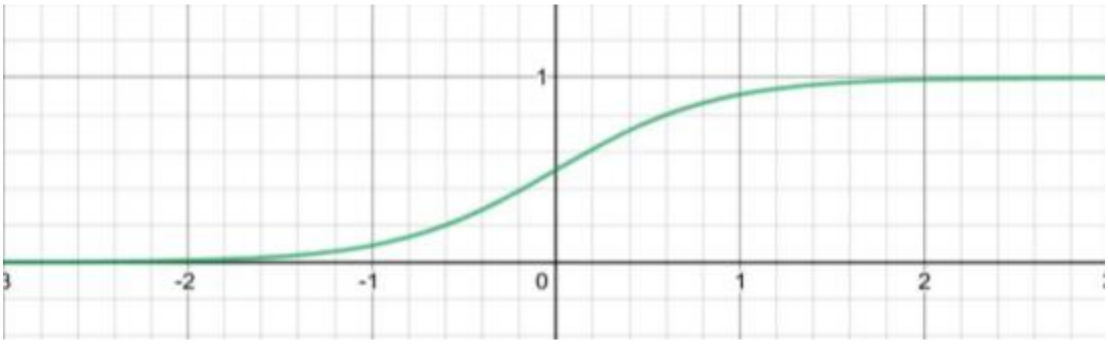
3.3 The Logit Model

The Logit model corrects the distortion created in the linear probability model and limits the probability of default between 0 and 1. The explained variable receives only two values: value 1 which represents a firm that has reached default and value 0 which represents a stable firm. This model uses financial and other variables to predict the firm's probability of default, and assumes that this probability has a logistical distribution, which is limited, by definition, to a range between 0 and 1:

$$f(z) = \frac{1}{1 + e^{-z_i}}$$

Which graph would look like Figure 4

Figure 4 Bounding function



Where for every possible value of z the outcome is always between 0 and 1. By combining the linear regression with the bounding function, we the following logistic regression model:

$$P(D = 1|Income, Employed) = \frac{1}{1 + e^{-(b0+b1\ Age+b2\ Income+\ b3\ Employed)}}$$

The general formulation of the logistic regression model then becomes.

$$P(D = 1|X1,...Xn) = \frac{1}{1 + e^{-(b0+b1\,X1...+bn\,Xn)}}$$

Subsequently

$$P(D = 0|X1,...Xn) = 1 - P(D = 1|X1,...Xn)$$

$$P(D = 0|X1,...Xn) = 1 - \frac{1}{1 + e^{-(b0+b1\,X1...+bn\,Xn)}}$$

$$P(D = 0|X1,...Xn) = \frac{1}{1 + e^{(b0+b1\,X1...+bn\,Xn)}}$$

Where D=1 in case of default and 0 otherwise.

$$\frac{P(D = 1|X_1, ... X_n)}{P(D = 0|X_1, ... X_n)} = e^{(b0+b1\,X1...+bn\,Xn)}$$

In terms of odds or

$$\ln\left(\frac{P(D = 1|X_1, ... X_n)}{P(D = 0|X_1, ... X_n)}\right) = b0 + b1\,X1 ... + bn\,Xn$$

In terms of log odds

Since logistic regression is linear in the log odds (logit) it basically estimates a linear decision boundary to separate both classes.

To interpret a logistic regression model, one can calculate the odds ratio. Suppose variable Xi increases with one unit with all other variables being kept constant (ceteris paribus); then the new logit becomes the old logit with added. Likewise. the new odds become the old odds multiplied by $e^{ßi}$. The latter represents the odds ratio—that is, the multiplicative increase in the odds when x, increases by 1 (ceteris paribus). Hence,

bi> 0 implies $e^{ßi}$ >1 and the odds and probability increase with Xi.
bi< 0 implies $e^{ßi}$ < 1 and the odds and probability decrease with Xi.

Another way of interpreting a logistic regression model is by calculating the doubling amount. This represents the amount of change required for doubling the primary outcome odds. It can be easily seen that for a particular variable Xi, the doubling amount equals.

Logistic regression is a very popular credit scoring classification technique due to its simplicity and good performance. Just as with linear regression, once the

parameters have been estimated. the regression can be evaluated in a straightforward way,
contributing to its operational efficiency.

3.4 Emerging Trends and Future Directions:

The progress made in machine learning and artificial intelligence (AI) is significantly influencing the trajectory of credit scoring in the future. The aforementioned technologies facilitate advanced examination of credit information, encompassing intricate patterns and non-linear correlations. The utilization of machine learning algorithms has the capability to effectively analyze extensive quantities of data and detect concealed patterns, thus enhancing the precision of credit risk evaluations.

The practice of credit scoring is undergoing a transformation as it integrates alternative data sources that go beyond the conventional credit data. Possible academic rewrite: The sources of information that can be used for various purposes may encompass diverse types of data, such as payments of utility bills, records of renting activities, profiles on social media platforms, and transactional data. Through the utilization of varied datasets, lenders can acquire a more all-encompassing comprehension of a borrower's creditworthiness.

The increasing prevalence of machine learning models has led to a rising demand for transparency and interpretability, which is addressed by the concept of Explainable AI. The objective of explainable AI techniques is to offer elucidation on the decision-making process of models in the context of credit assessment, thereby mitigating apprehensions regarding impartiality, partiality, and adherence to regulatory standards.

The process of credit scoring is of utmost importance in the context of lending decisions, as it enables lenders to evaluate the creditworthiness of potential borrowers and effectively mitigate credit risk. The utilization of a judgmental approach presents a degree of adaptability, however, it is susceptible to partialities and incongruities. Conversely, the statistical methodology offers impartiality and expandability, albeit it may not comprehensively encompass idiosyncratic situations. Through the integration of these methodologies, creditors can arrive at better-informed credit evaluations, achieving a harmonious equilibrium between professional expertise and data-derived perspectives. The anticipated progression of credit scoring is poised to integrate machine learning, alternative data sources, and explainable artificial intelligence methodologies, as technology continues to advance. The implementation of these technological developments is expected to improve the precision and impartiality of credit evaluations, resulting in advantages for both creditors and debtors.

4. PD model

4.1 Introduction

Based on the preceding chapter, it has been established that credit scores serve as a reliable metric to assess the level of risk that borrowers may pose to creditors. Default probabilities, commonly referred to as PDs, are standardized measures of likelihood that represent credit ratings. The range of these measures varies from zero to one. A score of zero denotes the impossibility of an event, whereas a score of one signifies its inevitability. Loans are commonly assigned a probability of default (PD) within a range of 0 to 30 percent.

The probability of default (PD) is a crucial parameter in credit risk analytics that undergoes rigorous examination and is also subject to the minimum standards mandated by prudential regulators. Financial institutions have a duty to include and exclude specific risk factors in their computations. Furthermore, there exists a requirement for minimum floors, specifically three basis points, to ensure a non-negligible probability of default (PD) for low default portfolios. This subject matter will be further elaborated upon in subsequent sections of this manuscript. Furthermore, it is imperative for financial institutions to validate their PD estimations through rigorous techniques, as discussed in the dedicated chapter on validation.

4.2 Default events

A PD describes the likelihood of a default event. Banks observe whether a borrower default and indicate this with a default flag-indicator.

$$D_{it} = \begin{cases} 1 & \text{borrower } i \text{ defaults at time } t \\ 0 & \text{otherwise} \end{cases}$$

The D describes the likelihood of a default event box observe whether borrowers default and generally indicate this with a default indicator (J. Crook, 2010).

It is postulated that the default event is stochastic in nature, and as such, an uppercase letter D is employed to denote the random variable, while its realization is represented by a lowercase letter d. An event that is not specified by the user can be designated as a default event, which can be selected from any (but not limited) of the events that are available.

- Payment delinquency of a number of days or more: popular thresholds are 30, 60, and 90 days
- Bankruptcy of the borrower
- Collateral owned by a bank (e.g., real estate owned after an unsuccessful sale
- a foreclosure auction)
- Foreclosure of loan
- Short sale of loan
- Loss/write-down amount
- Involuntary liquidation
- Debt modification as a positive interest, expense, or principal forgiveness

It is plausible to consider alternative default definitions, such as the Basel definition, which utilizes a threshold of 90 days or more for payment delinquency. (H. Hamerle, 2006)

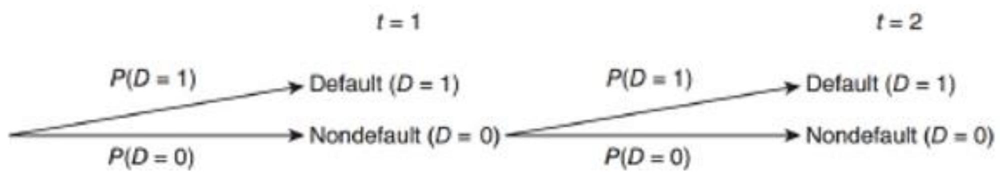
4.3 Conditional and Unconditional Default

Financial institutions monitor the progress of loans over a period and incorporate dynamic data into their evaluations. Temporal data may encompass borrower, loan, and collateral details (idiosyncratic data), as well as macroeconomic circumstances (systematic data). Assessment periods are typically categorized as short-term or long-term, with common examples including daily, monthly, quarterly, or annual intervals. The selection of a particular time frame may be contingent upon the accessibility of data and the requirements of interested parties such as depositors, investors, supervisory authorities, or equity holders. The evaluation of credit risk provides support to multiple functional areas within a bank. Certain domains, such as capital allocation and risk reporting in accordance with Basel, necessitate the estimation of risks for the upcoming period. Conversely, other domains, such as loan loss provisioning under IFRS 9, encompass multiple periods, frequently spanning the entire lifespan of financial instruments.

Figure 5 illustrates the contingency of default occurrences over a span of two time periods. Default events are typically considered as conclusive occurrences, whereby a default event in a particular period is contingent upon the survival (i.e., non-default) in preceding periods.

Financial institutions assess the likelihood of default (PD) for both parties involved, and the financial instruments utilized. As previously stated, the nomenclature of default probability is commonly employed to denote the default probability for a single period. Alternative expressions employed are the conditional default probability (given survival) and default intensity.

Figure 5 Default during two distinct time periods



In addition, it is possible to calculate multiyear default probabilities by using unconditional default probabilities and implementing them in multiyear assessments, which is a common practice in the computation of anticipated present values or loss values for financial instruments. The probability of default that is not subject to any conditions is frequently employed as a metric for assessing the probability of default from the standpoint of the loan's inception. The measure of the probability of default under specific conditions, such as survival, is commonly referred to as conditional probability of default. This metric is frequently employed to assess risk subsequent to origination. The probabilities of default, both conditional and unconditional, are equivalent during the initial period.

Assuming that a borrower has the same condition probability of default $PD_{t-1,t}$ and any t-1, t, we can omit the borrower index i. The unconditional probability of default $UPD_{t1,t2}$ can then be computes as follows

$$
\begin{aligned}
UPD_{t1,t2} &= S(t1) - S(t2) \\
&= \prod_{t=1}^{t_1}(1 - PD_{t-1,t}) - \prod_{t=1}^{t_2}(1 - PD_{t-1,t}) \\
&= \prod_{t=1}^{t_1}(1 - PD_{t-1,t}) - \prod_{t=1}^{t_1}(1 - PD_{t1,t})\prod_{t=1}^{t_2}(1 - PD_{t-1,t}) \\
&= \prod_{t=1}^{t_1}(1 - PD_{t-1,t})\left(1 - \prod_{t=1}^{t_2}(1 - PD_{t-1,t}\right) \\
&= S(t1)PD_{t1,t2}
\end{aligned}
$$

Where S(t) is the cumulative survival probability of the borrower

4.4 Basel Requirements

Banks frequently assign rating classes to borrowers and subsequently calculate default probabilities for these rating classes as a means of ascertaining regulatory capital requirements.

The default rating for Corporates, central governments, and central banks should solely consider the likelihood of obligor default. It is recommended that there be a minimum of seven ratings accessible for non-default obligors and a single rating for defaulters. In the context of retail exposures, it is imperative that a credit rating accurately captures the risks associated with both the obligor and the transaction. Therefore, it is imperative to consider the attributes of credit products and the degree of collateralization. It is advisable to steer clear of an overabundance of obligors within a given rating. It is advisable to ensure that ratings exhibit a high degree of homogeneity with respect to the risk of default. There is no suggested minimum number of ratings for retail exposures.

It is necessary to furnish a probability of default (PD) for each rating category with regards to corporate entities, central governments, central banks, and retail exposures. It is important to acknowledge that the terminology used to denote ratings may vary based on the specific geographic location, with alternative terms including pools, segments, grades, classes, or clusters. According to the definition, a defaulter is an individual or entity that is deemed unlikely to fulfill their financial obligations or has exceeded a period of 90 days past the due date. In the United States, the duration has been established as either 120 or 180 days, contingent upon the exposure class. In the context of the United Kingdom, it is common to utilize both the 90-day and 180-day timeframes. A lower limit of three basis points has been established for the probability of default. When obligors default, it can be inferred that the probability of default (PD) is 100 percent. In order to derive the probability of default (PD), it is recommended to utilize a minimum of five years of past data. However, it is imperative to note that not all data points should be accorded equal significance, particularly in instances where older data may be deemed less pertinent. The estimation of the probability of default (PD) for a specific rating can be achieved by computing the long-term mean of the one-year default rates.

4.5 Parameter Estimation

It is a widely held belief that default events are influenced by a latent data-generating process (DGP). The process by which data is generated remains elusive and has been the subject of extensive research aimed at comprehending its fundamental constituents. Numerous models have been suggested in scholarly works, with the (Metron, 1974)model being a prevalent one for corporate debtors. The model under consideration exhibits default when the market value of the assets, or their return, drops below the market value of the outstanding debt. The derivation of a one-year default probability from a structural model is demonstrated in Figure 6. It is commonly assumed in academic literature that the distribution of asset value adheres to a lognormal distribution, while the distribution of asset return is assumed to follow a normal distribution. In this chapter, the natural logarithm of x is denoted as log(x) and e raised to the power of x is represented as exp(x). The latent process can be utilized to model the standardized asset return, Air, of borrower i during time period t. In the event that the return of the asset AAAA falls below a certain threshold, a default event is triggered. The probability of default (PD) then becomes:

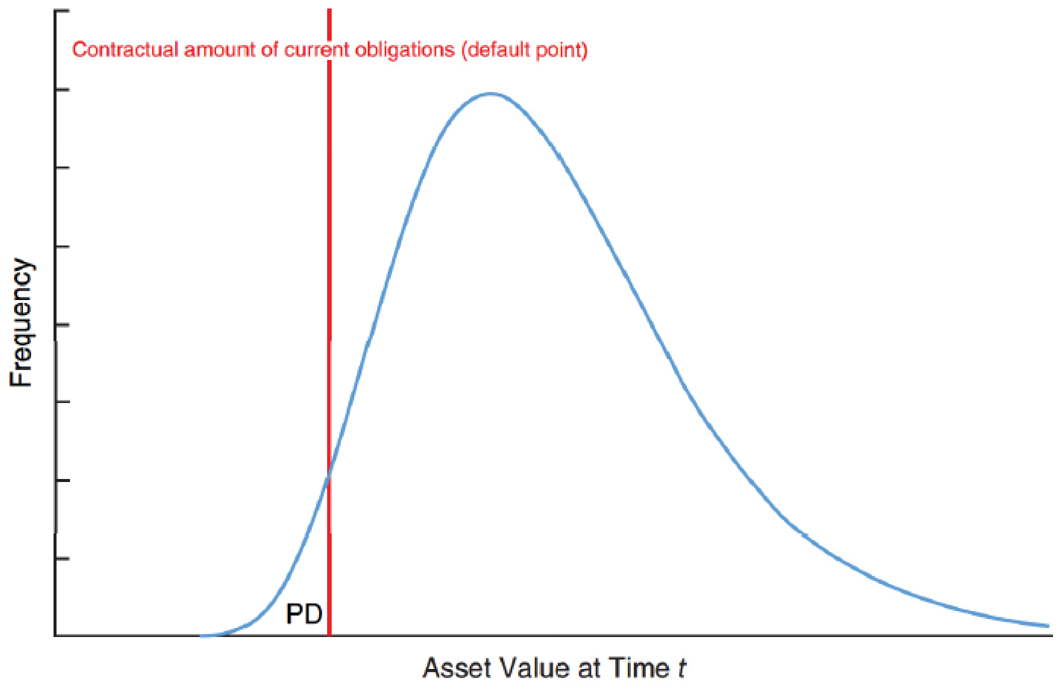
$$PD_{it} = P(D_{it} = 1) = P(A_{it} < \gamma_{it}) = \Phi(\gamma_{it})$$

with Φ being the cumulative density function of the standard normal distribution.

The credit model employed yields a probit model, wherein the linear predictor is denoted as "γ_{ij}". Alternative models could be developed to cover diverse risk segments and distributions, including consumer loans. The former pertains to the financial assets of a consumer, while the latter refers to a predetermined limit that, once exceeded, triggers a default occurrence. (H. Hamerle, 2006) formulated a logit regression model by utilizing an asset value return/threshold model. The forthcoming chapter on credit portfolio risk and default correlation will involve an expansion of the model through the partitioning of asset value returns into two distinct components, namely systematic and idiosyncratic.

The default event refers to the observable outcome. Regression models have been implemented in the banking sector to establish a correlation between the discernible default/nondefault result and the data that is accessible during the risk evaluation process.

Figure 6 Merton Model



Credit risk modelers employ observable data, including the creditor's earnings, debt, and liquidity, among other factors, to estimate the structural model. This model involves comparing the asset value to the debt value, also referred to as the distance to default. The concept of parameters pertains to the degree of sensitivity of observable outcomes to observable information, while a link function, which may be in the form of a linear combination or a nonlinear link, is posited.

Later in the discussion, econometric techniques for estimating parameters will be addressed. The curriculum will encompass the presentation of discrete-time and continuous-time (survival) models. Discrete-time models elucidate the occurrence of default event during a specific time interval, whereas survival models gauge the duration until default. There exists a strong correlation between these methodologies.

Various estimation techniques are commonly used, such as the unconditional mean of default indicators for single or multiple periods, regression techniques that condition default probabilities on observable variables (e.g., linear regressions for averages of default indicators), and nonlinear regressions for the default indicator itself. These methods are widely recognized in the field. Typically, these methodologies rely on maximum likelihood estimation methods that seek to optimize a theoretical likelihood function for the observed dependent variable, taking into account the available information variables and estimated parameters.

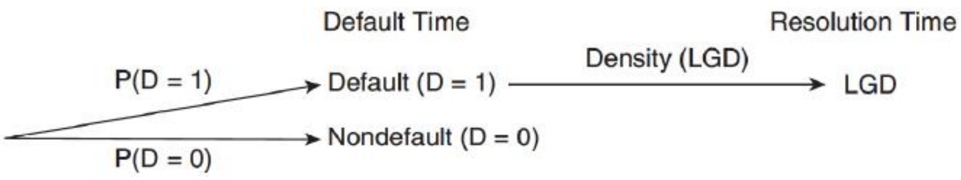
The values of estimated parameters are susceptible to uncertainty in the parameters themselves. The majority of estimation methodologies provide parameter estimates along with their corresponding standard deviations (also known as standard errors) and covariance/correlation matrices. Commonly, these are predicated on the supposition of a Gaussian distribution, where the parameter estimation is the approximated mean, and the standard error is the approximated standard deviation.

5.LGD model

5.1 Introduction

This chapter introduces models for loss given default (LGD) and recovery estimation. It is important to note that a loss arises only in the event of default and is conditional on the default event; hence it is called loss given default. Figure 7 shows that loss is conditional on the default events and that the loss given default is a continuous variable with density f. LGDs are commonly expressed as a ratio and related to the outstanding amount or exposure at default (EAD). In other words, LGD is essentially a loss rate given default. The recovery rate is then 1 — LGD.

Figure 7 Conditionality of LGD



5.2 Definition of Default

In order to unambiguously quantify the loss given default, you first need to have a well-framed definition of default. For a thorough discussion, see (Van Gestel, 2009). For non-retail exposures, rating agencies such as Moody's, Standard b Poor's (S&P), and Fitch use definitions of default that, although to a large extent overlapping, are not identical. Hence, if you use different definitions of default, then of course you cannot compare the resulting default and loss rates. More specifically, there is a direct interrelation between the default definition, the default rates, and the loss or LGD values. Hence, when LGD rates are reported, it is always important to ask for the default definition to be adopted, to make sure you can correctly interpret and benchmark them.

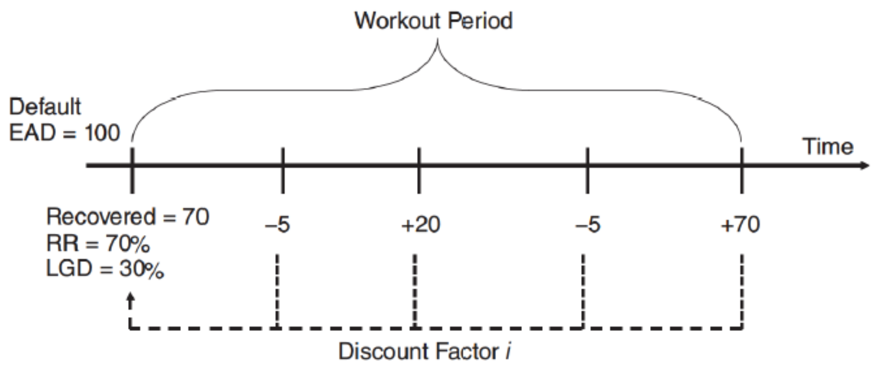
Usually, a bank will distinguish among different types of defaults. An operational default is due to technical issues on the obligor side. For example, an obligor is accidentally late when making the payment. A technical default is a default due to an internal information system issue. For example, the payment was made on time, but on the wrong account. A real default is a default due to financial problems or insolvency. These are the defaults we are interested in when modeling LGD. In case of default, various actions can take place. First, there can be a cure. This means a defaulter will pay back all outstanding debt and return to a performing or thus no-defaulter status with no accompanying loss. There could also be a restructuring or settlement, whereby the bank and the defaulter work out a recovery or repayment plan. The latter could, for example, result in an extension of the loan maturity to reduce the monthly installment amount. This usually comes with medium loss. Finally, there could also be liquidation, repossession, or foreclosure, which implies that the bank takes full possession of the collateral asset, if available, and sells it by starting up a bankruptcy procedure. Depending upon the value 01 the collateral, this may come with a high loss. When modeling LGD, it is of key importance that the default definition used is the same as for PD because PD and the LGD will be combined to calculate both expected and unexpected loss. Note that changing the default definition simultaneously impacts both the PD and the LGD. If you would, for example, relax the default definition from 90 days to 60 days in payment arrears, then the default rates and PD may increase, but the loss rates and LGD may decrease. Hence, the combined effect in terms of expected loss stays relatively constant. Cures are those defaulters that become non-defaulters and return to performing by repaying all outstanding debt. The corresponding LGD will thus be zero, or close to zero. As already mentioned, note that this depends on the default definition. Relaxing the definition of a default, for example from 90 to 60 days, will typically increase the number of cures. In case of multiple defaults, you could opt to include only the last default event and also relate the PD and EAD to this.

5.3 Definition of LGD

The ratio of the loss on an exposure resulting from an obligor's default to the amount outstanding at default may now be used to determine the loss given default. As a result, it is the recovery rate's complement; in other words, LGD is equal to 1 minus the recovery rate. It's important to notice that LGD emphasizes economic loss rather than accounting loss in this case. Therefore, when creating the LGD, all expenses as well as possible advantages must be appropriately taken into consideration. The expenses of realizing the collateral value, the administrative costs of mailing collection letters or calling the defaulting obligor, legal fees, and time delays in what is recovering are a few examples of costs. Benefits like interest on past-due amounts, fines for delays, or other commissions may also be taken into account. The workout technique, which is utilized for both corporate and retail exposures, the market approach, the assumed historical LGD approach, and the corporate exposures implied market approach are some of the several ways that LGD may be quantified. We will go through each of these in greater depth in the sentences that follow.

The exercise technique, which is routinely used for both corporate and retail exposures, is the most widely used way for determining LGD. Working up the collection procedure for defaulted exposure and closely examining the incoming and departing cash flows are the goals here. Consideration should be given to both direct and indirect cash flows. The running expenses of the fitness department are an example of indirect expenditure. The loss should then be calculated by discounting these cash flows to the point of default. Figure 8 is a condensed example.

Figure 8 Workout Period of LGD



Assume that an exposure with an EAD of $100 defaults. The collection department will get in touch with the defaulting debtor as soon as possible, either by phone or by mailing a collection letter. Let's estimate that this will cost $5. The obligor then pays back $20, which is obviously insufficient to pay off the whole balance. Therefore, the collection department pays $5 to get in touch with the debtor once again. Suppose the debtor doesn't respond, at which point the bank chooses to realize the collateral and receives $70 in exchange. Using a discount factor, which we leave unspecified at this time, we can now discount all of these cash flows back to the point of default. Let's assume that the discounted sum is $70. Due to the discounting that has been used, this amount is less than the total of the four digits, which comes to $80. In other words, this indicates that $70 of the $100 EAD has been recovered, giving a recovery rate of 70% and an LGD of 30%.

The market technique can be used as an additional LGD measurement method. Examining companies who filed for bankruptcy but still have debt securities, such bonds or loans, trading on the market is the aim here. The bonds will turn into trash bonds after the bankruptcy event, and investors will start trading them depending on how much they anticipate recovering from the insolvent company. This method looks at the market price (for instance, one month after the bankruptcy or default occurrence) to give the market some time to settle and take in all the information. The recovery rate is then approximated by this market price, allowing for the computation of the LGD as I less the recovery rate. Keep in mind that this strategy is ineffective for exposures from the retail market because it only applies to debt instruments that trade on the market. In its LossCalc tool, Moody's adopted this strategy (G. Gupton, 2005) The PD estimations and observed losses are used to calculate the inferred LGD in the implied historical LGD approach. In other words, it first determines the expected loss before using the formula EL = PD • LGD. The predicted loss divided by the PD may then be used to calculate the LGD.

The assumed market LGD methodology is another method for calculating LGD. We haven't seen much application of this very theoretical strategy in the sector. Asset pricing models like structural or reduced form models are used to examine the market price of hazardous bonds that have not yet defaulted. The spread over the risk-free rate, which represents the anticipated loss, is then located, and the LGD is backed out from here. The fact that the market price contains risk aversion premiums in addition to the credit risk and is only partially influenced by it is among the major drawbacks of this strategy.

Finally, the Basel Capital Accord specifies that economic loss is the definition of loss utilized in assessing LGD. This implies that any cash flow or expense associated with the default should be appropriately taken into account, as was already indicated. Estimates of the LGD are required by the Accord for the foundation internal ratings based (IRB) method. Applying to corporations, governments, and banks is as follows: A 45 percent LGD will be assigned to senior claims against corporations, governments, and banks that aren't protected by recognized collateral. As stated in Basel Committee on Banking Supervision's 2006 report (Supervision, 2006), all subordinated claims on corporations, governments, and banks shall be given a 75 percent LGD.

5.4 Computing Observed LGD

When calculating observed Loss Given Defaults (LGDs) from workout cash flow observations, several challenges arise, including:

- *It is recommended that the dataset encompasses a full business cycle at minimum.*
- *It is necessary to establish a clear definition for the workout or resolution period.It is imperative to address incomplete workouts.*
- *It is necessary to establish a clear definition for the discount rate.*
- *LGDs (low-grade dysplasia) beyond the typical range necessitate appropriate management.*

- *It is recommended to incorporate indirect costs.*

Subsequently, we will provide a detailed explanation for each of these points. Upon consideration of the components, the calculation of the loss given default (LGD) is derived by subtracting the present value of all cash flows, encompassing internal expenses, from the exposure at default (EAD). This is achieved through the utilization of the cash flow (CFC) and discount rate (r) for time t. Illustratively, let us contemplate an initial Exposure at default[2] (EAD) of $100,000, accompanied by the cash flow sequence depicted in Table 1 EAD and Cash flowsTable 1

Table 1 EAD and Cash flows

	Default Date	Year 1	Year 2	Year 3
EAD	*100,000*			
Cash flows		*5,000*	*7,000*	*10,000*

The computation of LGD can be performed after the completion of the workout process, specifically after the third year. Assuming a discount rate of 3% per annum, the present value at the time of default will be

$$\sum_{t=1}^{T} \frac{CF}{(1+r_t)^t} = \frac{5000}{1{,}03} + \frac{7000}{1{,}03^2} + \frac{10}{1{,}03^3} = 19{,}749$$

$$LGD = \frac{EAD - \sum_{t=1}^{T} \frac{CF}{(1+r_t)^t}}{EAD} = \frac{100{,}000 - 19{,}749}{100{,}000} = \frac{80{,}251}{100{,}000} = 0.80251 \text{ or } 80.25\%$$

[2] Exposure at Default (EAD) will be cover in the later chapter.

5.4.1 Cash Flows

5.4.1.1 Recoveries

Cash recoveries pertain to the tangible monetary inflows that are anticipated to be retrieved from delinquent debtors throughout the workout duration. The traceability of cash recoveries is facilitated by the fact that relevant particulars are usually documented in one or multiple financial institution databases. An additional type of form pertains to non-monetary recoveries, which encompasses the repossession of collateral or the restructuring of loans to assist borrowers in fulfilling their payment obligations. The handling of noncash recoveries is frequently conducted on an individual basis. The classification of recoveries can also be based on their origin, which includes product, collateral, guarantee, and residual (unsecured). The concept of product recoveries pertains to the practice of trade credit, wherein the outstanding balance can be diminished if the underlying goods are readily and expeditiously sold to purchasers. The process of collateral recoveries encompasses the assessment of collateral values through appraisal, the expenses incurred in holding the collateral, and the liquidation of the collateral. It should be noted that a single collateral has the potential to be pledged for multiple facilities. Therefore, it is recommended that the allocation of collateral recovery be tailored to each individual facility. The allocation methodologies can be predicated on either the pledge value or the exposure at default (EAD) of each facility. The process of guarantee recoveries entails the involvement of a third party who is willing to assume responsibility for paying a portion or the entirety of the outstanding balance in the event of a default. It should be noted that guarantees may have either a close or distant relationship with the borrower. When a close relationship exists between entities, such as parent companies, guarantees may be considered as mitigating factors for potential credit default. In the absence of borrower guarantees, they are categorized as Loss Given Default (LGD) mitigants, implying that they do not impact the likelihood of default, but rather offer assistance in the event of default. Unsecured recoveries refer to residual portions of assets that financial institutions can potentially recover subsequent to the retrieval of products, collateral, and guarantees.

5.4.1.2 Costs

As previously stated, LGD denotes the financial detriment incurred. Therefore, it is imperative to consider indirect costs in a comprehensive manner, as exemplified by the subsequent citations:

The Committee of European Banking Supervisors (CEBS) (Supervision, 2005) published a report in 2005.

"Workout and collection costs should include the costs of running the institutions collection and workout department, the cost of outsourced services and all appropriate percentage of other ongoing costs, such as corporate overhead".

The Federal Register of 2007 (Register, 2007):

"Cost data comprise the material direct and indirect costs associated with workouts and collection."

Federal Register of 2007 (Register, 2007),

"Material indirect costs, costs of running the collection and workout department, costs of outsourced services, appropriate percentage of overhead must be included"

The current inquiry apply to the methodology of incorporating these consequential expenses. It is evident that indirect expenses are not monitored on an individual basis for each defaulter, but rather necessitate computation at a collective level. Many financial institutions engage in a minor accounting procedure to determine the indirect cost rate. An example is presented Table 2. Assuming a time frame of four consecutive years, specifically from 2010 to 2013. The second column denotes the aggregate exposure at default. At the conclusion of the year, measurements were taken of the workout files. It should be noted that due to the extended duration of the workout period, many of the figures presented in the analysis may contain instances of double counting. Stated differently, the figure of 1,500 recorded in 2011 encompasses certain data points that were previously captured in the 1,000 figure recorded in 2010. The subsequent column denotes the quantity recuperated annually. There is an absence of instances of double counting in this context. Ultimately, the ultimate column denotes the combined internal expenses incurred for exercising on an annual basis. This encompasses various expenses such as the operational costs of the workout department, remuneration of its personnel, electricity charges, computer hardware and software expenditures, among others.

Table 2 Workout costs

Year	EAD	Annual Recovered During Year	Internal Workout Cost Per Year
2010	1,000	250	20
2011	1,500	500	28
2012	800	240	12
2013	1,250	360	27

It is now possible to compute two different rates of cost. The initial approach employs the exposure at default as the denominator. The premise underlying this statement is that greater default risk exposure results in increased expenses associated with workout. Currently, the calculation of the cost rate can be performed either through a time-weighted or pooled approach. The time-weighted cost rate can be defined as the quotient obtained by dividing the aggregate workout costs for all years by the exposure at default, thereby yielding an average value. In this instance, the calculation is derived from 1/4 multiplied by the sum of 20 out of 1,000, 28 out of 1,500, 12 out of 800, and 27 out of 1,250, resulting in a value of 1.8 percent. The cost allocation method known as pooled cost rate involves the division of the total cost of all workouts by the aggregate value of all exposure units. The summation of the values, namely 20, 28, 12, 1,500, 800, and 1,250, results in a percentage of 1.91. One drawback associated with utilizing this cost rate is that it necessitates multiplication by the duration of the exercise session, expressed in years. An alternative method for determining the cost rate involves utilizing the recovered amount as the denominator. The underlying premise of this statement is that there is a positive correlation between the expenses associated with a workout and the level of recovery required. The cost rate can be calculated using either a time-weighted or pooled approach. The time-weighted cost rate refers to the mean value of the expenses incurred during the workout period, divided by the corresponding recovery amounts, across all years. In the given instance, the expression is represented as the sum of four fractions, namely 1/4, 28/500, 12/240, and 27/350, which yields a result of 6.5 percent. The cost pooling rate is obtained by dividing the total expenses incurred for all exercises by the total amount of revenue recovered. In the present scenario, the aforementioned calculation results in a percentage of 6.49, derived from the summation of 20, 28, 12, 300, 240, and 330. One benefit of this methodology is its independence from the duration of the exercise regimen, as each quantity was recuperated within a single year. Therefore, this is a more straightforward approach to execute.

5.4.1.3 Discount Factor

As previously stated, LGD serves as a measure of financial detriment. Thus, it is imperative to consider the time value of money while measuring the LGD. The present value of one dollar is greater than its future value. Therefore, it is advisable to implement discounting. An essential challenge in the implementation of discounting pertains to the establishment of an appropriate discount rate. As per the directives of the Basel Committee on Banking Supervision (Supervision, 2005) the discount rate must comprise of the time value of money and a risk premium for undiversifiable risk.

"When recovery streams are uncertain and involve risk that cannot be diversified away, net present value calculations must reflect the time value of money and a risk premium appropriate to the undiversifiable risk. In establishing appropriate risk premiums for the estimation of LGDs consistent with economic downturn conditions, the bank should focus.
on the uncertainties in recovery cash flows associated with defaults that arise during the economic downturn conditions. When there is no uncertainty in recovery streams (e.g., recoveries derived from cash collateral), net present value calculations need only reflect the time value of money, and a risk free discount rate is appropriate."

Several discount rate methodologies have been suggested in scholarly literature (Maclachalan, 2004).

- Contract rate
- Weighted average cost of capital (WACC)
- Return on equity (ROE)
- Market return on defaulted bonds
- Equilibrium returns based on the capital asset pricing model (CAPM)

A comparative research study conducted by Global Credit Data has revealed that the WACC and equilibrium approaches are viable techniques for capturing the time value of money and systematic risk. The employment of the contract rate is a prevalent practice, notwithstanding its susceptibility to censure due to its association with the pricing at the inception stage. Therefore, it fails to account for the prevailing interest rate and price of systematic risk during default and is unsuitable for distressed scenarios that may impact the recovery of cash flows. The identification of discount rates as a potential cause of inconsistencies in risk weighting across financial institutions has been a recent development. The current scenario, coupled with the historical low levels of interest rates, has led certain prudential regulators to contemplate the implementation of minimum floors. As per the statement provided by the Prudential Regulation Authority of the United Kingdom (Authority, 2015)

" It is expected by the Prudential Regulation Authority (PRA) that firms take measures to ensure that the discount rate utilized for the estimation of loss given default (LGD) is not lower than 9%."

The ongoing debate surrounding discount rates notwithstanding, there are significant advantages to be gained from the implementation of risk-sensitive discount rate models that align with the systematic risk that underpins the occurrence of losses.

5.4.1.1 Workout Period

The duration of the workout period may fluctuate based on the credit type, the workout policy implemented by the financial institution, and the regulatory framework in the locality. Additional insights on this matter have been offered by regulatory bodies such as the Bank of International Settlements (BIS) and the Hong Kong Monetary Authority (HKMA) . The workout period may terminate under various circumstances, such as when the unrecovered value reaches below 5 percent of the EAD, upon repossession of the collateral one year after default, or upon the sale of the debt to a collection agency. Typically, financial institutions have a workout period ranging from two to three years. Bet, Kellner, and Rösch (J. Bertz, 2016) conducted a study that involved an international comparison of workout periods.

5.4.1.2 Incomplete Workouts

The matter of incomplete workouts has been briefly addressed previously. The phenomenon of incomplete workouts pertains to obligors who have defaulted and are currently undergoing the workout process. Several regulatory bodies have issued additional guidance regarding incomplete exercise routines. The regulation of the Committee of European Banking Supervisors (Supervision, 2005) in 2005 first referenced the aforementioned organization, which is now known as the European Banking Authority (EBA).

“Institutions should incorporate the results of incomplete workouts as data/information into their LGD estimates, unless they can demonstrate that the incomplete workouts are n 0t relevant. “

Part Of this was copied by the Prudential Regulation Authority (PRA) (Authority, 2015)Of the United Kingdom as follows:

“In order to ensure that estimates ECDs take into account the most up to date experience, we would expect firms to take account of data in respect of relevant incomplete workouts, i.e., defaulted exposures for which the recovery process is still in progress, with the result that the final realized losses in respect of those exposures are not yet certain.”

The latest regulation from EU does not provide any additional information regarding incomplete workouts. There are several approaches that can be taken to address incomplete workouts. One potential initial approach is to compute the extant Loss Given Default (LGD) for an unfinished exercise routine and employ it as the ultimate Incomplete-Gradient Descent (I-GD) metric within the dataset. The approach being employed is highly conservative, resulting in an upwardly skewed estimation of the Loss Given Default (LGD) metric. Stated differently, employing this methodology would result in an overestimation of the Loss Given Defaults (LGDs) due to the potential occurrence of supplementary recoveries in the future. It should be noted that certain banks have demonstrated a tendency to consistently overlook recoveries beyond a period of three to five years when conducting their LGD calculations. An alternative approach involves the utilization of proficient or anticipatory models that gauge the ultimate Loss Given Default (LGD) of an unfinished workout by taking into account diverse features such as the date of default, the proportion of already collected amount, the time of collection, and other relevant factors. One straightforward approach is to exclude incomplete workouts and solely incorporate fully completed workouts in the data set utilized for LGD modeling. This methodology is frequently employed in practical applications. Survival analysis can be employed to account for censored variables, such as loss amount. It should be noted that this concept is predominantly theoretical in nature and is not frequently implemented within the industry (Stoyanov, 2009).

5.4.1 Business-Cycle

The data set used for LGD modeling should cover at least a complete business cycle. The obvious question that follows is: What is a business cycle? Preferably, the data should include one or two downturn periods. This will be handy lor the LGD calibration as we will discuss later. Note that you do not need to attach equal importance to each year of data. Hence, if you think data of five or seven years ago is less relevant today, you can attach a lower weight to it. Downturn periods are generally defined as periods with negative GDP growth _ Hence the number of years Of data required depends on the analyzed economy. For example, Japan has been in an extended economic downturn period since 1993 whereas Australia has not experienced an economic downturn since 1991.

6. EAD model

6.1 INTRODUCTION

This chapter provides an overview of exposure at default (EAD) modeling, the Basel requirements for EAD, and the different techniques employed in constructing FAD models. It is important to note that similar to LGD, the expected loss and Basel capital are also linearly affected by EAD. Therefore, it is crucial to precisely depict the modeling of EAD.

To commence, it is imperative to establish a clear definition of the EAD modeling concept. The FAD, or Funded Amount Due, pertains to on-balance-sheet exposures such as mortgages, term loans, and installment loans. It is characterized as the nominal outstanding balance, which is adjusted for specific provisions. Stated differently, it denotes the total amount of unpaid debt.

Studies on EAD have been conducted (Jacobs, 2011), which involved the development of linear regression models to analyze conversion measures for a corporate revolving credit facility. The models incorporated various determinants, including credit rating, utilization, tenor, industry, and macroeconomic factors. The most noteworthy discovery is that the utilization factor has the greatest impact on FAD. A 2012 analysis (I. Barakova, 2012) pertains to syndicated corporate credit lines. The study conducted by the authors reveals that the risk rating, line utilization, size, and sudden turns in the economic cycle are the most influential factors affecting the exposure at default (EAD). Agarwal, Ambrose, and Liu (S. Agarwal, 2006) conducted an analysis on the utilization of home equity lines of credit using private bank data. A study conducted by Tong et al (E.N. Tong, 2016)) examines the effectiveness of EAD in relation to credit card loans. A comprehensive elaboration of this study will be provided subsequently. Another study (Valvonis, 2008) provides an illustration of the assessment of exposure at default for regulatory capital.

6.2 Fixed versus Variable Outstanding

The EAD exhibits determinism in certain loan categories, such as numerous corporate bonds, while it displays variability in others. The variable "with" can be categorized into two distinct types, namely credit lines and loans that offer flexible payment schedules. Credit lines, such as those associated with credit card loans, typically come with a predetermined limit and a corresponding amount that has been drawn. The borrower has the ability to utilize the line of credit up to the predetermined maximum amount. Upon the conclusion of a designated time frame, the recipient of the loan is obligated to reimburse the utilized sum, subsequently resetting the balance to a neutral state. Loans that offer flexible payment schedules typically include provisions for prepayment and redraw options. In the context of loans, such as mortgage loans, amortization typically necessitates that borrowers make payments towards both the interest and principal amounts prior to the loan's maturity. As the principal amount is repaid, the loan balance decreases accordingly.

The prepayment option enables the borrower to make payments exceeding the scheduled amount, whereas the redraw option permits the borrower to access prepayments and/or principal repayments. In certain nations, such as Australia, it is customary to establish a pair of linked accounts, namely a loan account characterized by a negative balance and an offset account featuring a positive balance. The residual debt is determined by subtracting the sum of the two balances, and individuals have the ability to access funds from the offset account at their discretion, with payments towards the principal being allocated to said account. The aforementioned product enables borrowers to access prepayments through a redraw facility. In various nations, including the United States, it is customary to secure a home equity line of credit in conjunction with a mortgage loan. The objective is to restructure extant principal payments onto a distinct account, where the limit is determined by using the value of the property minus the primary mortgage as collateral. Additional agreements for extracting home equity comprise of reverse mortgages, which may possess redrawn characteristics as well.

6.3 Off-balance-sheet Exposures

As previously noted, financial institutions are subject to off-balance-sheet risk. The category of off-balance sheet exposures encompasses contingent credit exposures, such as credit guarantees and loan commitments, as well as counterparty credit risk pertaining to over-the-counter (OTC) derivative agreements on future deliveries that are conducted on a bilateral basis. The Exposure at Default (EAD) is contingent upon the loss incurred in correlation with a guarantee or an unfavorable shift in an underlying metric, in combination with the credit event of a counterparty in derivative agreements. In the context of off-balance-sheet exposures, it is imperative to consider the proportion of the undrawn amount that is anticipated to be transformed into credit in the event of a default by the reference entity or individual (in the case of a guarantee) or the counterparty (in the case of a derivative).

6.4 Conversion Measures

One possible approach to modeling exposures at default is to construct a model for the exposure amount or a monotonic transformation of it. One possible approach is to establish a correlation between the EAD and a scaling factor, and subsequently calculate conversion metrics based on this relationship. According to Yang and Tkachenko's (2012) research, it has been observed that conversion measure models exhibit greater robustness compared to EAD models. This is attributed to the fact that conversion measure models standardize all observations to a common denominator.

Table 3 Conversion Factors

Conversion Measure	EAD Calculation
Credit Conversion Factor (CCF)	EAD= Drawn amount +CCF*(Limit-Drawn)
Credit Equivalent (CEQ)	EAD= Drawn amount +CEQ*(Limit)
Limit Conversion Factor (LCF)	EAD=LCF*Limit
Used Amount Conversion Factor UACF	EAD=UACF*Drawn

Illustrated in Table 3 are four prevalent conversion measures. Additional strategies for converting specified amounts and limits, along with other numerical values, could be contemplated. Illustrations of such variables comprise revenue, workforce size, profitability, solvency, or chronological age.

The definition of the credit conversion factor (CCF) pertains to the proportion of the unused funds that will be transformed into credit. It should be noted that the remaining balance available for withdrawal is equivalent to the credit limit subtracted by the amount already withdrawn. The Effective Advance Determination (EAD) is calculated as the sum of the drawn amount and the Credit Conversion Factor (CCF) multiplied by the difference between the limit and the drawn amount. The definition of credit equivalent (CEQ) pertains to the proportion of the limit that is anticipated to be transformed into credit. The Expanded Available Drawdown (EAD) is mathematically expressed as the sum of the drawn amount and the product of the Credit Equivalent Amount (CEQ) and the limit. The Loan Equivalent (LEQ) or Limit Conversion Factor (LCF) is mathematically expressed as a ratio between the total exposure and the limit. The EAD can be mathematically expressed as the product of either the Loss Given Default (LCF) or the Loss Frequency (LFQ) and the limit. The definition of the used amount conversion factor (UACF) is established with the drawn amount serving as the point of reference. Therefore, the Expected Annual Default (EAD) is calculated by multiplying the Utilization Adjusted Credit Factor (UACF) with the amount that has been withdrawn. It is imperative to exercise caution in the selection of these measures. There exists a certain degree of controversy surrounding the utilization of conversion measures, as they have been deemed excessively restrictive (R. Taplin, 2007)or prone to volatility (Qi, 2009)

6.5 Regulatory framework of EAD

The Basel Accord typically employs the credit conversion factor (CCF) methodology. The Credit Conversion Factor (CCF) is a numerical value that varies between zero and one. This value is associated with an Exposure at Default (EAD) that is equivalent to the amount drawn and the limit, respectively. The process of EAD modeling currently involves the estimation of the CCF. Certain financial institutions refrain from creating CCF models and instead adopt a cautious strategy by uniformly establishing the CCF to a value of one. Stated differently, it is assumed that the exposure at default will invariably be equivalent to the credit limit in the case of EAD. Subsequently, we will examine Basel's perspective on the modeling of EAD. According to the Basel Committee on Banking Supervision in 2006, paragraph 3.10 of the Basel II Accord pertains to the exposures of corporations, sovereigns, and banks.

For off-balance sheet items, exposure is calculated as the committed but undrawn amount multiplied by a CCF. There are two approaches for the estimation of CCFs: a foundation approach and an advanced approach.

It is important to note that the IRB methodology comprises two distinct sub-approaches, namely the foundational IRB approach and the advanced IRB approach. Under the foundation Internal Ratings-Based (IRB) approach, financial institutions have the ability to independently estimate the Probability of Default (PD). However, they must depend on either the Accord or local regulatory bodies for benchmark values of the Loss Given Default (LGD) and Exposure at Default (EAD). The advanced

Internal Rating-Based (IRB) approach enables the bank to assess all three risk parameters, namely the Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). It is important to note that the foundational Institutional Review Board (IRB) methodology is not permissible for retail exposures. Paragraph 83 of the Basel Committee on Banking Supervision 2006 (Supervision, 2006) provides the reference values for EAD or CCF for corporate, sovereign, and bank exposures in relation to loan commitments.

Credit conversion factors (CCFs) of 20% and 50% will be applied to commitments with an original maturity up to one year and commitments with an original maturity over one year, respectively. Commitments that can be canceled by the bank without prior notice will receive a 0% credit conversion factor (CCF).

Paragraph 334 of the Accord pertains to retail exposures.

Both on- and off-balance sheet retail exposures are measured gross of specific provisions or partial write-offs. The EAD on drawn amounts should not be less than the sum of (i) the amount by which a bank's regulatory capital would be reduced if the exposure were written-off fully, and (ii) any specific provisions and partial write-offs.

Subsequently, paragraph 335 ensues after the aforementioned paragraph.

For retail off balance sheet items, banks must use their own estimates of CCFS .

Paragraph 336 addresses the matter of ensuring a uniform definition of EAD and LGD in the following manner:

For retail exposures with uncertain future drawdown such as credit cards, banks must take into account their history and/or expectation of additional drawings prior to default in their overall calibration of loss estimates. In particular, where a bank does not reflect conversion factors for undrawn lines in its EAD estimates, it must reflect in its LGD estimates the likelihood of additional drawings prior to default. Conversely, if the bank does not incorporate the possibility of additional drawings in its LGD estimates, it must do so in its EAD estimates.

In summary, it is possible to incorporate supplementary illustrations before default in either the Loss Given Default (LGD) or Exposure at Default (EAD) metrics. Nevertheless, it is a prevalent convention to incorporate them in the EAD delineation through the utilization of credit conversion factors, as previously deliberated.

The concept of a margin of conservatism and economic downturn EAD is also incorporated in the regulations of the EU and U.S. This is intended to address the potential volatility of EAD over the economic cycle. It is noteworthy that this bears a striking resemblance to LGD.

In the context of over-the-counter derivatives, the level of risk exposure is determined by considering both the present exposure and the potential future exposure. Historically, the effective aggregate notional amount for over-the-counter derivatives was calculated as the combination of the replacement cost, also known as the current exposure or RC, and the potential future exposure, or PFE. The calculation of PFE involved the multiplication of the notional amount by a corresponding CCF obtained through reference to a predetermined table, which was contingent upon the underlying class and maturity. The regulations are set to undergo revisions in the standardized methodology for evaluating counterparty credit risk exposures, commonly referred to as SA-CCR, as outlined by the Basel Committee on Banking Supervision in 2014 (Supervision, 2014). In accordance with these regulations, the level of exposure is determined through the following calculation:

The equation EAD = 1.4(RC+ PEE) is a mathematical expression used to calculate the expected loss of a credit portfolio.

The replacement costs incorporate margining, which involves the counterparty providing cash or collateral. The assessment of potential future exposure encompasses various characteristics that delineate the risk profile of the derivatives. One issue of a pragmatic nature. One potential issue with EAD models, irrespective of whether they are utilized for modeling EAD, a derivative transformation, or a conversion measure, is the possibility of underestimating the EAD in comparison to the present outstanding or drawn amount. Therefore, it is common practice to utilize a flooring approach when calculating EAD for regulatory objectives. The EAD, or exposure at default, is equivalent to the greater value between the drawn amount and the product of the LCF and the limit. In other words, the EAD is always at least as large as the drawn amount.

Regarding the Credit Conversion Factor (CCF), a negative value can arise if the debtor has repaid a fraction of the outstanding debt before the occurrence of default. It is advisable to round down a negative CCF to zero for the purpose of estimation.

It is possible for the CCF to surpass a value of one. This phenomenon may arise as a result of alterations in credit limits or offline transactions that permit borrowers to surpass their credit limit in exceptional circumstances. Stated differently, the limit conveyed to the client is a flexible threshold that may be exceeded on occasion. When the CCF exceeds one, there is an inverse relationship between the drawn balance and the exposure, where an increase in the drawn balance leads to a decrease in the exposure. This can be exemplified with a concise illustration. Assuming a credit limit of $2,500 and a cash conversion factor (CCF) of 10%, the following can be inferred. When the balance that has been drawn reaches a value of 1,000, the Exposure at Default (EAD) increases to 2,650. In the event that the balance drawn is equivalent to 1,500, the level of exposure is observed to decrease to 2,600. It is advisable to maintain the CCF within the range of zero to one. Employing a rigid credit limit that is impervious to surpassing is a viable approach to guarantee that the value remains consistently below unity. The establishment of a rigid credit limit may be determined through the analysis of past data or by employing a confidence level, if deemed necessary.

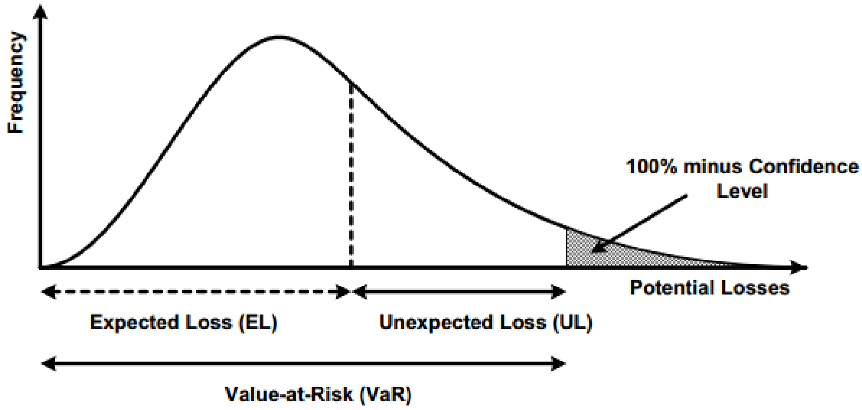
7.CREDIT RISK PROTFOLIO AND RWA

7.1 INTRODUCTION

Banks hold large portfolios of loans and, similarly to asset management, correlations or more generally dependencies are the main drivers of the rtsk of the portfolio. A bank commonly uses credit portfolio models to make assessments about the risks of a portfolio in terms of probability distributions of potential credit losses. Popular approaches used in the industry include actuarial and mathematical, as well as models that use computer simulations for generating the loss distribution, Usually, the ovt• come of such a model is a highly skewed probability distribution for the potential losses of the portfolio, as shown in Exhibit 9.1. The distribution is often characterized by some important parameters, namely the expected loss (EL), the value at risk (VaR, which is a quantile), and the conditional value at risk (CVaR) or expected shortfall (ES), which is the expectation of the losses that are greater than the value at risk. The expected loss is typically covered by provisions. The required economic capital for the bank to stay solvent is then the difference between the VaR and the expected loss (or CVaR and expected loss). Let Li be the random loss for a credit risky instrument i where i = , nina certain time period. The portlolio loss is then the sum over the losses 01 all instruments (i.e., L = Li). Let F(L) be the cumulative distribution function (CDF) of L. The risk measures then become:

$$E(L) = E\left(\sum_{i=1}^{n} L_i\right)$$

Figure 9 Loss Distribution



Although there are different models used in the industry, a seminal paper by Gordy (Gordy, 2003) showed that the most widely applied approaches can be unified and, if adequately parameterized, yield very similar results. Therefore, in this chapter we focus on one particular specification, which is widely used in practice and also implememed in Ille Basel for regulatory capital.

The model underlying the IRB approach is shown in Figure 9. Regulators base the capital requirement on the value at risk calculated using a one-year time horizon and a 99.9% confidence level. They recognize that expected losses are usually covered by the way a! financial institution prices its products. (For example, the interest charged by a bank on a loan is designed to recover expected loan losses.) The capital required is therefore the value at risk minus the expected loss. The value at risk is calculated using the one-factor Gaussian copula model of time to default. Assume that a bank has a very large number of obligors and the i-th obligor has a probability of default equal to PDi. The copula correlation between each pair of obligors is ρ[3]. As in Section 11.5, we dene

$$\mathrm{WCDR}_i = N\left[\frac{N^{-1}(\mathrm{PD}_i) + \sqrt{\rho}N^{-1}(0.999)}{\sqrt{1-\rho}}\right]$$

where WCDRi denotes the "worst-case default rate" defined so that the bank is 99.9% certain it will not be exceeded next year for the *i*-th counterparty. (Gordy, 2003) research shows that for a large portfolio of instruments (loans, loan commitments, derivatives, and so on) that have the same ρ, in a one factor model the one-year 99.9% VaR is approximately13

$$\sum_i \mathrm{EAD}_i \times \mathrm{LGD}_i \times \mathrm{WCDR}_i$$

where EADi is the exposure at default of the ith counterparty and LGDi is the loss given default for the *i*-th counterparty. The variable EADi is the dollar amount that is expected to be owed by the *i*-th counterparty at the time of default during the next year. The

[3] Note that the Basel Committee publications use *R*, not ρ, to denote the copula correlation.

variable LGDi is the proportion of EADi that is expected to be lost in the event of default. For example, if a bank expects to recover 30% of the amount owed in the event of default, LGDi = 0.7. The expected loss from defaults is

$$\sum_i \mathrm{EAD}_i \times \mathrm{LGD}_i \times \mathrm{PD}_i$$

The capital required in Figure 15.1 is the excess of the 99.9% worst-case loss over the expected loss. It is therefore

$$\sum_i \mathrm{EAD}_i \times \mathrm{LGD}_i \times (\mathrm{WCDR}_i - \mathrm{PD}_i)$$

PD: The probability that the counterparty will default within one year (expressed as a decimal)

EAD: The exposure at default (in dollars)

LGD: The loss given default or the proportion of the exposure that is lost if there is a default (expressed as a decimal)

When the correlation ρ is zero, WCDR = PD because in that case there is nondefault correlation and the percentage of loans defaulting can be expected to be the same in all years. As ρ increases, WCDR increases

7.2 Corporate, Sovereign, and Bank Exposures

In the case of corporate, sovereign, and bank exposures, Basel II assumes a relationship between the correlation parameter, ρ, and the probability of default, PD, based on empirical research.14 The formula is

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

Because exp(−50) is a very small number, this formula is to all intents and purposes

$$\rho = 0.12\left(1 + e^{-50\times \mathrm{PD}}\right)$$

As PD increases, ρ decreases. The reason usually given for this inverse relationship is as follows. As a company becomes less creditworthy, its PD increases and its probability of default becomes more idiosyncratic and less affected by overall market conditions. The relationship between WCDR and PD in

Table 4 WCDR and PD relationship

PD	0.10%	0.50%	1%	1.50%	2%
WCDR	3.40%	9.80%	14.00%	16.90%	19.00%

WCDR is, as one would expect, an increasing function of PD. However it does not increase as fast as it would if ρ were assumed to be independent of PD. The formula for the capital required for the counterparty is

$$\text{EAD} \times \text{LGD} \times (\text{WCDR} - \text{PD}) \times \text{MA}$$

The meaning of the first three terms in this expression should be clear from our earlier discussion leading to equation (15.7). The variable MA is the maturity adjustment and is defined as

$$\text{MA} = \frac{1 + (\text{M} - 2.5) \times b}{1 - 1.5 \times b}$$

where

$$b = [0.11852 - 0.05478 \times \ln(\text{PD})]^2$$

M being the maturity of the exposure. The maturity adjustment is designed to allow for the fact that, if an instrument lasts longer than one year, there is a one-year credit exposure arising from a possible decline in the creditworthiness of the counterparty as well as from a possible default by the counterparty. (Note that, when M = 1, MA is 1.0 and has no effect.) The risk-weighted assets (RWA) are calculated as 12.5 times the capital required so that the capital is 8% of RWA, 4% of which must be Tier 1.
Under the Foundation IRB approach, banks supply PD while LGD, EAD, and Mare supervisory values set by the Basel Committee. PD is subject to a floor of 0.03% for bank and corporate exposures. LGD is set at 45% for senior claims and 75% for subordinated claims. When there is eligible collateral, in order to correspond to the comprehensive approach that we described earlier, LGD is reduced by the ratio of the adjusted value of the collateral to the adjusted value of the exposure, both calculated using the comprehensive approach. For derivatives, the EAD is calculated in a manner similar to the "current exposure plus add-on" approach of Basel I and includes the impact of netting. M is set at 2.5 in most circumstances. Under the advanced IRB approach, banks supply their own estimates of the PD, LGD, EAD, and M for corporate, sovereign, and bank exposures. The PD can be reduced by credit mitigants such as credit triggers. (As in the case of the Foundation IRB approach, it is subject to a "oor of 0.03% for bank and corporate exposures.) The two main factors infuencing the LGD are the seniority of the debt and the collateral. In calculating EAD, banks can with regulatory approval use their own models. In the case of derivatives, the model is likely to involve a Monte Carlo simulation to determine how expected exposure (after netting and collateral) will vary over the next year. The capital given by equation (15.9) is intended to be sufficient to cover unexpected losses over a one-year period that we are 99.9% certain will not be exceeded. (As discussed earlier, the expected losses should be covered by a bank in the way it prices its products.) The WCDR is the default rate that (theoretically) happens once every thousand years. The Basel committee reserved the right to apply a scaling factor (less than or greater than 1.0) to the result of the

calculations in equation (15.9) if it fnds that the aggregate capital requirements are too high or low. A typical scaling factor is 1.06.

$$RWA = 12.5 \times EAD \times LGD \times (WCDR - PD) \times MA$$

8. Conclusion

In conclusion, the utilization of credit risk modeling and Internal Ratings-Based (IRB) models holds significant importance within the financial sector, as it offers a comprehensive structure for measuring and overseeing credit risk. Financial institutions utilize models that integrate statistical techniques and expert judgment to estimate crucial risk parameters including the Probability of Default (PD), Loss Given Default (LGD), and Exposure at Default (EAD). The aforementioned parameters hold significant importance in the determination of regulatory capital requirements as per the Basel Accords and in the process of making well-informed lending decisions.

Notwithstanding their extensive usage and apparent advantages, credit risk models and IRB models are not devoid of constraints. A significant obstacle lies in the dependence on past data for the calibration of models. Although historical data can serve as a valuable point of departure, it may not comprehensively encompass forthcoming risks, particularly in light of evolving economic circumstances or exceptional occurrences such as the recent COVID-19 pandemic. This underscores the significance of subjecting systems to stress testing and the necessity of employing adaptable models that can accommodate alterations in circumstances.

Model risk is a significant challenge that stems from the possibility of model inaccuracies or misapplication. The occurrence of this phenomenon can be attributed to a multitude of factors, which may encompass inaccurate presumptions, inaccuracies in data, or unsuitable application of the model. In order to address the potential risks associated with models, it is imperative to establish robust model governance protocols, which entail periodic model validation and impartial evaluation.

Moreover, the matter of the quality and accessibility of data must also be considered. The acquisition of precise and all-encompassing data is imperative for the successful development of credit risk models. However, in numerous instances, such data may be deficient or arduous to procure. This assertion holds particularly true for portfolios with low default rates, as the limited availability of default data can pose significant difficulties in the calibration of models.

Finally, it should be noted that the intricacy of Institutional Review Board (IRB) models can have both positive and negative implications. Although it permits a more intricate comprehension of credit risk, it may also result in a dearth of transparency and challenges in interpreting model outcomes. This highlights the necessity of unambiguous communication and instruction to guarantee that both model users and stakeholders possess a comprehensive understanding of the model's capabilities and constraints.

Prospectively, the domain of credit risk modeling is anticipated to persistently develop in reaction to novel challenges and prospects. The progressions in technology, such as the development of artificial intelligence and machine learning, present promising prospects for enhancing model precision and efficacy. Nevertheless, these advancements also give rise to novel concerns regarding the interpretability and impartiality of models, which will require resolution.

In brief, although credit risk modeling and Internal Ratings-Based (IRB) models are efficacious instruments for credit risk management, they are not devoid of obstacles. Through the recognition of these constraints and the persistent pursuit of enhancement, we may aspire to render superior and well-informed judgments when confronted with indeterminate circumstances. As the financial environment undergoes changes, it is imperative that we adapt our methods of comprehending and handling credit risk.

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