Supply Chain-Based Creditworthiness

Small and Mid Corporate Rating

A dissertation submitted to the faculty
of the School of Industrial and Information Engineering
DEPARTMENT OF MANAGEMENT, ECONOMICS AND INDUSTRIAL ENGINEERING
of Politecnico di Milano
in partial fulfilment of the requirements for the degree
of Master of Science

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December 2017

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The standard approach to company rating too frequently neglects the importance of supply-chain related variables for the assessment of creditworthiness. Small and medium enterprises, for various reasons, are often penalized by overly financial performance-oriented risk models. In fact, shifting this paradigm is not only in the interest of borrowers: bad loans are a renowned plague in the banking world, nevertheless in Europe. Improving the approach to small corporate credit risk assessment will indeed contribute to mitigate this issue. Restrained access to funding for small and medium enterprises (SMEs) strongly impacts not only companies but the society as well, in that these actors represent the biggest employer in the market.

Supply chain literature recognize the importance of connections among supply chain actors for appraising enterprise risk. On one hand, distressed supply chain environments can impact financial performances of a good borrowers while, on the other, quantitatively estimating relationships with commercial partners can yield information on a borrower's status.

Better models can contribute to elicit hidden supply-chain information, thus bridging information asymmetries that raise the cost of financing. Reducing uncertainties from the lending side can renew trust among parties, leading to a virtuous circle to the benefit of the whole economic system.

In light of these considerations, this work develops two frameworks that show how supply chain-related performances can be effective predictors of probability of default (PD). From the methodological perspective, the dissertation highlights the potentialities of machine learning as a powerful tool for credit risk assessment, which allows to extract additional - potentially untapped - knowledge from few and unconventional data features. Our promising results shall stimulate researchers and practitioners in casting their more efforts in this directions.

Acknowledgements

A sincere appreciation goes to my supervisors, Antonella and Mihalis, for their guidance along the last 12 months, for the precious feedbacks and for the deserved critics which contributed to the value of this work.

First and foremost, I would like to thank my parents for their abiding support throughout this whole endeavour: sure this has not always been effortless, I did not take it for granted. Thank you.

I wish to thank the rest of my family as well. Particularly my nonna and my nonno for their unconditional love: probably nothing can compare to the care and the kindness I have been gifted from you.

Thanks to the friends of a lifetime and to the ones for the life. Thanks for the patience, for the listening and for telling me off: in fact the only thing I am sure I to have truly deserved, anytime.

Grazie.

Gab

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Glossary

Asset Class A group of securities that exhibits similar characteristics, behaves similarly in the marketplace and is subject to the same laws and regulations.

Basel Accords Banking supervision Accords - Basel I, Basel II and Basel III - issued by the Basel Committee on Banking Supervision (BCBS). They are called the Basel Accords as the BCBS maintains its secretariat at the Bank for International Settlements (BIS) in Basel, Switzerland and the committee normally meets there.

Capital Adequacy Capital requirement (also known as regulatory capital or capital adequacy) is the amount of capital a bank or other financial institution has to hold as required by its financial regulator. This is usually expressed as a capital adequacy ratio of equity that must be held as a percentage of risk-weighted assets.

Collateralized Loan Obligation A form of securitization where payments from multiple middle sized and large business loans are pooled together and passed on to different classes of owners in various tranches. A CLO is a type of collateralized debt obligation.

Credit Default Swap Financial hedging instrument. An agreement for which the seller of the CDS will compensate the buyer (very often usually the creditor of the reference loan) in the event of a loan default (by the debtor) or other credit event.

Creditworthiness The ability to borrow money. The better one's creditworthiness, the more likely it is that a bank or other financial institution will extend credit.

Default In finance, a default is the failure in meeting legal obligations of a loan.

Exposure An exposure (alias financial asset) is the amount of money that can be lost in an investment.

Financing Gap A measure of the perceived difference at firm level between the need for external funds (across all channels, i.e. bank loans, overdraft, trade credit, equity and debt securities) [39].

Funding Gap *see* Financing Gap.

K-Means Another simple clustering algorithm. It aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi Diagram cells.

K-Nearest Neighbours Among the simplest clustering algorithms. It classifies observations based on a similarity measure (e.g., distance functions). KNN has been used in statistical estimation and pattern recognition already in the beginning of 1970's as a non-parametric technique.

Linear Discriminant Analysis A method used in statistics, pattern recognition and machine learning to find a linear combination of features that characterizes or separates two or more classes of objects or events.

Markovian process A random process whose future status is independent from the past ones, given its present status.

Maximum Likelihood Estimator A method of estimating the parameters of a statistical model given observations, by finding the parameter values that maximize the likelihood of making the observations given the parameters.

Non Performing Loan An exposure that satisfy either or both the following criteria [34]

- It is more than 90 days past-due;
- The debtor is assessed as unlikely to pay its credit obligation in full without realisation of collateral, regardless of the existence of any past-due amount or of the number of days past due.

Overfitting A modeling error which occurs when a function is too closely fit to a limited set of data points. It generally takes the form of making an overly complex model to explain idiosyncrasies in the data under study.

Payment-in-kind Financial instrument that pays interest or dividends to investors of bonds, notes or preferred stock with additional securities or equity instead of cash.

Poisson distribution A discrete probability distribution that models the probability of a given number of events occurring in a fixed time interval if these events occur with a known constant rate λ and independently of the time since the last event.

Probability of Default A financial term describing the likelihood of a default over a particular time horizon. It provides an estimate of the likelihood that a borrower will be unable to meet its debt obligations.

Sensitivity Test sensitivity is the ability of a test to correctly identify true positives.

Small/Medium enterprise According to European Union (EU) jurisdiction, SME are defined by to two parameters: staff headcount and one between turnover and total assets [24].

Particularly:

- A medium enterprise employs 249 and 50 people with a turnover ranging from €10 million to €50 million or a total asset between €43 million and €10 million

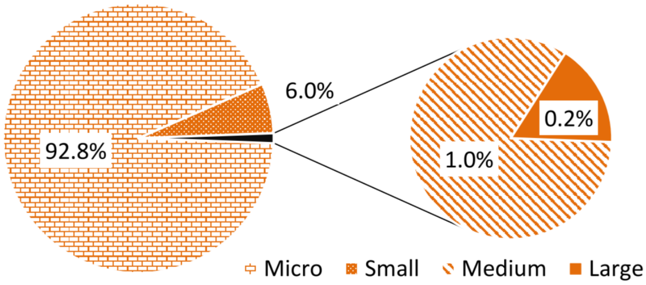


Figure 1: Eurostat, National Statistical Offices and DIW Eco

- A small enterprise's staff is between 49 and 10 employees with turnover/total assets in the range from €10 million and €2 million
- Staff headcount smaller than 10 and with turnover/total assets not greater than €2 million defines the boundaries of micro enterprises.

SMEs represent the 99.8 percent[1] of the Non Financial Corporations (NFCs) in the EU (see figure 1), accounting for 67 percent of the employment and almost 60 percent of the generated added value. Without considering the category of micro enterprises, SMEs outnumber larger corporations by a factor of 36.

Specificity Test specificity is the ability of the test to correctly identify true negatives.

Voronoi Diagram Partitioning of a plane into regions based on distance to points in a specific subset of the plane.

[1]Micro 92.8 percent; small 6.0 percent; medium 1.0 percent

Acronyms

AIRB Advanced-IRB

ANOVA Analysis of VAriance

AP Accounts Payables

AR Accounts Receivables

AUC Area Under Curve

BCBS Basel Committee on Banking Supervision

BIS Bank for International Settlements

CCR Corporate Credit Risk

CDS Credit Default Swap

CLO collateralized loan obligation

COGS Cost Of Goods Sold

CRA Credit Rating Agency

CRF Credit Risk Factor

DTC Digital Trade Chain

EAD Exposure at Default

ECAI External Credit Assessment Institution

ESMA European Securities and Market Authority

EU European Union

FIRB Foundation-IRB

HH Household

I Inventories

ICT Information Communication Technology

IDE Integrated Development Environment

IRB Internal Rating-Based

IT Information Technology

KNN K-Nearest Neighbours

KPI Key Performance Indicator

LDA Linear Discriminant Analysis

LGD Loss Given Default

M Maturity of an exposure

mbbls One thousand of Barrels (of Oil)

mboe One thousand of Barrel of Oil Equivalent

MLP Multilayer Perceptron

mmboe One million of Barrel of Oil Equivalent

NFC Non Financial Corporation

NOWC Net Operating Working Capital

NPL non performing loan

OECD Organisation for Economic Cooperation and Development

OLS Ordinary Least Square

PD probability of default

PIK Payment-in-kind

PLT Production Lead Time

RAM Random Access Memory

RC Regulatory Capital

ROC Receiver Operating Characteristic

RWA Risk Weighted Asset

SA Standardized Approach

SC Supply Chain

SCF Supply Chain Finance

SCM Supply Chain Management

SF Supporting Factor

SL Specialized Lending

SME Small/medium enterprise

VAT Value Added Tax

VBA Visual Basic for Applications

Part I

Introduction

Chapter 1

Two Problems

Access to credit is an issue for several SMEs. Albeit the problem traditionally affects OECD countries, where the SMEs financing gap amounts to around $1 trillion and the two thirds of the firms are either unserved or underserved [62], the same issue persists in developed markets as well.

Indeed, the problem is two-folded: on one hand, these firms struggle in satisfying lenders' requirement to be eligible for financing; on the other side, financial providers experience severe difficulties in assessing the creditworthiness of these actors, resulting in frequent non performing loans (NPLs).

This work will emphasise the idiosyncrasies of the EU environment.

1.1 From the Perspective of a Small-Medium Enterprise

Amongst the most pressing problems among SMEs, access to finance is reported by 10 percent of the SMEs as the most significant issue and it is statistically more felt the smaller the firm [78]. The increasing need for capital is corroborated by the generalized increase of inventories, net working capital and fixed investments over the last 3 years. Under a financing perspective, the trend is for the reduction of the debt-to-assets ratio, in favour of a lower relative dependence from debt capital.[1]

It is true that at EU level, slightly more than the half[2] of small and medium enterprises report diminishing interest expenses, whereas the net majority of micro firms still accounts an increase[3] for this indicator but, at any rate, both figures are in strong contrast with the same data for large enterprises, among which more than two businesses out of three[4] report a decrease in interest expenses. The fact is even more clear if considered that the scenario, with respect to the last semester 2015, has worsened for SMEs whilst improving for larger corporates.

Despite the level of interest rates is, on average, diminishing and the available size of loan or credit line slowly growing, the collateral requirementsand the other requirements to access credit financing have been constantly raising throughout the years, mostly due

[1] Debt capital includes: credit line, bank overdraft or credit card overdraft, leasing or hire-purchase, factoring, trade credit, bank loan, other loan, grant or subsidised bank loan, debt securities issued.

[2] Net 6 percent of respondents, i.e. 53 small and medium enterprises out of 100 who did not indicate the situation as "unchanged". This latter consideration holds for all the hereafter mentioned statistics

[3] Net 4 percent of respondents, i.e. 52 micro enterprises out of 100

[4] Net 34 percent of respondents, i.e. 67 large enterprises out of 100

to the increase in regulatory capital requirements introduced by the Basel Accords. If these warranties, on one side, represent an assurance for lenders, they clearly are an obstacle for borrowers. Particularly, out of the 15 percent of SMEs not deeming debt as a relevant source of financing, 1 firm out of 5 reports either:

- the non-availability of bank loans or
- the insufficiency of collateral/guarantee, or
- the excessive interest expenses or
- the disproportionate amount of paperwork involved in the process.

With specific reference to bank loans, less than 1 company out of 3 starts the application process and only the 7 out of 10 application are rewarded with the entire required amount of money, while the 7 percent of the applicants does not even meet the requirement to access to a part of the requested financing. The figures are alike for all the other forms of debt financing.
Anyway, the perceived funding gap is mildly improving[5] after being constantly worsening from the beginning of the crisis until mid-2014. Perhaps the phenomenon is partially due to the fact that 1 SME out of 10 reports no needs for any type of debt financing (increasing trend from previous years).

Still, the average interest rate for credit line and bank overdraft for SMEs remains twice as high as the one of large enterprises[6] [39] and [42] and, despite a positive growth, SME lending[7] remains far below its pre-crisis level [36].

1.2 From a Bank's Side

The weighted average NPLs ratio and FBLs ratio in the EU are respectively 5.7 percent and 3.5 percent.[8] Out of 28 EU countries, in 10 of them banks show average NPL ratios higher than 10 percent of which 6 (Cyprus, Greece, Slovenia, Portugal, Italy and Ireland), equal or greater than 15 percent. Though a NPL does not necessary implies default, the spread between NPL ratio and default ratio is, on average, only 2.7 percent, [37] meaning that almost every non performing loan ends with a default. Disaggregating data,[9], thus excluding HHs from the analysis , thus only considering NFCs, brings even more the issue forward. Particularly, 7 domicile countries have a NPL ratio for NFCs higher than 15 percent, if considering domestic banks, 6, considering foreign institution only. To these regards, foreign banks have on average, 3 percent lower NPL ratio, likely due to the advantageous corporate client selection operated by non-resident lenders [37]. Eventually, restricting the analysis to SMEs only – according to the last available data for the sector [35] – financial institutions report an alarming weighted non-performing loan (NPL) average ratio of 18.5 percent, with 17 out of 25 surveyed EU countries reporting 10+ percent NPL ratios.

[5] Net 3 percent of respondents, i.e. less than 52 SMEs out of 100
[6] Average interest rate for SMEs: 4 percent. Average interest rate for large enterprises: 2 percent
[7] Proxied by loans up to €1 million. Pre-crisis level: €95 billion; 2013/14 level: 54 million
[8] Aggregated data (NFCs + Households (HHs)) with huge variability across jurisdictions, mainly due to different impact of the financial crisis in 2008.
[9] New sample reduced to 19 EU countries

Chapter 2

Credit Rating and Probability of Default

Basel II accords require that every corporate exposure must be assessed on two rating dimension: the risk of borrower default and the transaction specific factors. The latter reflect peculiarities of each individual transaction, while the first must be consistent[1] for every exposure of the same borrower as a proxy of borrower's creditworthiness. This naturally brings to the need of the assessment of the creditworthiness for whatever entity in seek of external financing. According to the Basel regulatory capital framework, depending on the specific rule adopted by the financial provider, creditworthiness of the counterparties (i.e. the borrowers) can be either derived by an External Credit Assessment Institution (ECAI) or entirely estimated through bank's internal standards. In either case, the correct estimation of credit risk is the crucial element for the benefit both financial providers and borrowers. Particularly, the smaller, the more difficult is a correct estimation of said value.

ECAIs do not directly provide the PD estimation, but a credit rating, defined[2] as an opinion about credit risk, i.e. about the ability and willingness of an issuer, such as a corporation or state or city government, to meet its financial obligations in full and on time. Credit ratings may also speak to the credit quality of an individual debt issue, such as a corporate or municipal bond, and the relative likelihood that the issue may default, but for the purposes of this work we will focus solely on the credit risk of an issuer.

Since there are future events and developments that cannot be foreseen, the assignment of credit ratings is not an exact science and credit ratings are not intended as guarantees of credit quality or as exact measures of the probability that a particular issuer or debt issue will default, though the rating, in turn, can be translated into probability of default through the so called transition matrices: historical records of changes in credit rating of obligors within the same asset class, over a defined period. The application of transition matrices to convert ratings in PDs has been criticized from multiples reasons. On one hand, a transition matrix includes migration[3] probabilities records rating events for both period of economic expansion and downturn, therefore historical default probabilities

[1] Except in cases of country transfer risk and or changes in the borrower's grade

[2] Adapted from Standard & Poor's corporate website

[3] i.e. the probability to change rating class in a given amount of time. (where the lowest rating class correspond to the default state)

can hardly be indicative of the likelihood of future default events. On the other hand, the approach implicitly assumes that each obligor in the same rating class shows the same probability distribution of rating migration, i.e. that the probability of default would change only when the rating is upgraded, even if the opposite is clearly true. Both these assumptions have been proven to be inaccurate by numerical simulations, so that the actual rates can deviate significantly from historical average rates and transition probabilities.[4]

In fact, as it will be clearer in the following paragraphs, credit ratings not always ends up in an explicit estimation of the probability of default of the obligor. On the contrary, the PD, or credit risk, as it is defined in the Basel framework, is a punctual estimation of the default likelihood of a borrower within a predefined time frame. The difference has to be kept into consideration, even the two terms, in the following chapters will be used alternatively. When needed, it will be clarified in advance whether the subject is a generic obligor assessment or a punctual default likelihood.

2.1 Creditworthiness In the Supply Chain

The rationale for the focus on creditworthiness is, quite clearly, that the estimation of such parameter directly influences the willingness of a banking institution to provide credit to a corporate as well as the cost of said capital. The cost of debt is an increasing function depending from borrower's creditworthiness:

$$i = c_{\text{Funding}} + c_{\text{Operation}} + c_{\text{E[Loss]}} + c_{\text{Capital}} + \text{Negotiation Margin}$$

where the price of the loan i, i.e. the interest rate, depends on:

1. c_{Funding}: cost of borrowing from central bank. Fixed, does not depend on borrower's ratings

2. $c_{\text{Operation}}$: cost arising from a bank's operation (wages, rent). Fixed, does not depend on borrower's rating

3. $c_{\text{E[Loss]}}$: Premium for the estimated losses expected due to the default of the borrower in the future. Variable, depend on borrower's rating (lower for good ratings, higher for bad ratings).

4. c_{Capital}: return to be made on the capital that banks keep for economic and legal reasons with respect to unexpected losses. Variable, depend on borrowers' rating (lower for good ratings, higher for bad ratings).

5. negotiation margin: Additional margin over and above the cost (including cost of capital) the bank incurs for credit origination (may be negative in some cases). Variable, but it does not necessarily depend on borrowers' ratings.

Banks look at the rating throughout the entire lending process, from the loan assessment decision (go/no go), to the pricing of the loan and for the continuous assessment of their borrowers [40]. As this work is promoted by the Supply Chain

[4]KVM study.

Finance (SCF) Observatory of the university of the School of Management of Politecnico di Milano,in the following chapter, we will have an brief overview at some recent literature on the subject. Attention will be given to the effect on creditworthiness of operational performances and interactions of the focal enterprise with its surrounding business environment. The idea is that, as the financing opportunities of a company are mainly influenced by its credit rating, the securities and the willingness of the lender, SCF can lead to an improvement of the chances for the involved parties to successfully access money market [53].

2.2 Novel Approaches

Statistics on access to finance and NPL ratios, as showed in the previous section, bring forward all the shortcomings of the current rating systems, especially with respect to SMEs. In the light of these facts, and with a further look at the more (and less) conventional approaches on the subject, which will be introduced in the following part, the objective is to develop and assess the validity a novel approach to the SME rating, that could at least temper some of the principal drawbacks of the standard methods.

Part II

Literature Review

Chapter 3

Financial Supply Chain

3.1 Supply Chain Management

Supply Chain Management (SCM) is the integrating function with primary responsibility for linking major business functions and business processes within and across companies into a cohesive and high-performing business model. It includes all the logistics management activities, as well as manufacturing operations, and it drives coordination of processes and activities with and across marketing, sales, product design, finance, and information technology.[1] However, it is just in the last two decades that scholars have begun focusing on the impact on the role of financial flows in Supply Chain (SC).

The most recent approaches to the SCM disciplines look at the supply chain itself as a complex network [66], rather than as an ordered chain of supplier-buyer relationship. The globalisation of the market brings to longer and wider SCs. These can be seen as a connection of nodes representing trade exchanges, i.e. purchases and sales of good and services. If quality of goods, services and the information flows have always traditionally been the two core assumptions for the maintaining of the trade relationship, lots of problems arises when approaching the third element of the supply chain: financial flows. The financial supply chain is the set of principles aimed at aligning operation and financial flows, to determine the values of liquidity, accounts and working capital in a corporation. Unfortunately, financial supply chain is troubled with inefficiencies, resulting in an increase of the working capital of enterprises [18].

As a reference, Italian large companies recorded an average time to collect revenues of 96 days, while the European average is 53 days. This compares to an even longer time to settle commercial liabilities, a whopping 149 days, against a European average of 45 days. The Net Operating Working Capital (NOWC) of the top 2,050 companies in Italy sums up to over €100 billion. Such protracted payment times on the part of large companies inevitably have serious repercussions along the entire SC, especially for SMEs [81]. The inclusion of the working capital in the SCM equation, together with the increased globalisation of SCs, which non-linearly increase the points of interaction within the SC, highlights the need for a balance in requirements and processes, with the SC-wide objective to create stakeholder value and sustainable growth [18].

[1] Council of Supply Chain Management Professionals (https://cscmp.org)

3.2 Supply Chain Finance

Financial supply chain inefficiencies, stimulated the need for a collaborative management of financial flows within SCs. The SCF literature originates from these needs.

3.3 Definitions

Being a rather young discipline, different definitions of SCF have been given, without one being able to strongly prevails on the others. At any rate, it is possible to identify two main approaches: financial oriented and supply chain oriented [48]. Given the not perfect consistency of the literature, we choose a synthesis of the some of them as a term of reference.

According to some scholars [84], supply chain finance explores the optimisation of the cost of capital. They argue that the integration of the financing process with partners in the supply chain may be able to temper the three dimensions that affect the cost of capital:

1. the volume of the financing,
2. the duration of the financing and
3. the cost of the financing;

thus easing the access to capital to firm within the given SC. The rationale for this reasoning considers the issue of information asymmetries between SC agents and external financing providers, that can make convenient for a borrower to finance a project through the intermediation of another SC player, thus increasing the expected return on its investment. This is possible because a SC partner might be keen to finance the focal company at a lower interest rate than the external agent, due to alleged benefits stemming from the project is being financed. This applies both to asset financing as well as working capital financing.

As traditional commercial loans rely on fixed assets as securities, SCF is beneficial particularly to those SMEs that, often limited in fixed assets, cannot have easy access to the standard collateral-driven market. With SCF securities can be represented by liquid (non-fixed) assets, such as inventories and receivables, thanks to the improved access to information about material flows, that contributes to the reduction of the credit risk of the financial services [23].

Similar is the definition given by the practitioners, that looks at the SCF as the variety of approaches and instruments that optimize the transactions, working capital and costs of supply chains, thus significantly improving access to finance or reducing the need to finance by unlocking potential funding from within supply chains instead of relying on external creditors.[2]

3.4 The Importance of the Network

Facing the abovementioned SC network approach, the Supply Chain Finance Community has highlighted the attention on the opportunity for the development of novel SCF

[2]https://www.scfcommunity.org/what-is-scfc

solution involving tier-n suppliers/buyers.

Table 3.1 is an attempt to classify part of the traditional SCF literature according to the extent of the compliance to this view. Starting from a set of representative papers proposed by a previous literature review work [48], we will specify whether the subject has been tackled exclusively from a theoretical point of view or a supporting model has been developed.

Table 3.1: Supply Chain Finance Literature

#	Article	Multi-tier perspective	Multi-tier model
1	[53]	*Yes.* Supply Chain Finance is an approach for two or more organizations in a supply chain, including external service providers, to jointly create value through means of planning, steering, and controlling the flow of financial resources on an interorganizational level.	*No.* Purely theoretical speculations.
2	[18]	*Yes.* The supply chain is a network of participants that trade goods, services and information in front of purchase and sales orders. The financial component, expressed through invoices and	*No.* Single-level SCF solutions: • Letter of credit • Reverse factoring • Pre-shipment financing
3	[84]	*No.* The model includes two actors of a supply chain and an (external) financial market which offers both actors capital to unequal interest rates because of the differing company risks involved	*No.* Single-level model.
4	[23]	*No.* We consider a simple supply chain with a supplier and a retailer. The supplier produces a single product which retailer sells to customers.	*No.* Single-level model.
5	[71]	*No.* Despite a mention to the GVC, there are no references to multi-tiered model	*No.* Single-level SCF solutions: • Pre-shipment financing • VMI • Raw material inventory • Post-shipment financing • In-transit stock • Distribution financing

6	[50]	*Yes.* Supply chains are often so tightly coupled that the domino effect of suboptimal working capital management can lead to financial glitches at a single supplier and even bankruptcy. Thus, each working capital management decision should consider every upstream and downstream partner within the supply chain	*No.* Need to better understand the causes of balanced or unbalanced Cash Conversion Cycles (CCCs) along the supply chain and study the necessary information flows and incentives that would support a supply chain-spanning approach towards WC management. Future research could collect data from several stages in a supply chain
7	[99]	*Yes.* The use of pre-shipment financial supply management (FSCM) of the focal firm increases the use of pre-shipment FSCM of the supplier with its suppliers. The use of post-shipment FSCM of the focal firm reduces the propagation of liquidity shortages further up the supply chain.	*Yes.* Framework for the adoption of SCF solution, according to the dependence and the dispersion of suppliers, through WC analysis
8	[100]	*Unclear.* Multiple mention to the upstream supply chain, but the issue is never clarified.	*No.* Single
9	[77]	*No.* Mention to the increasing complexity of SCM due to network effects. Any reference to multi-tiered model	*No.* The developed model only tackles managerial challenges for SCF implementation

Despite all the articles mention the issues/challenges related to an intertwined SC, only some of them seem to truly approach SCF under this perspective and just one [100] attempts to deliver a model that would exploit the deepness of the supply chain as a driver for the adoption of specific SCF solutions.

Nonetheless, all the publications seem focusing on the benefit of relatively short-sighted SCF programmes, without notable mentions to the influence of the SC structure on the three determinants of the cost of capital. Moreover, the perspective of the financing entity, is very often neglected, as if it was deemed unimportant by these scholars.

Coherently with the issue highlighted above, some studies have explicitly tried to model the network factor for the evaluation of SCF initiatives, but besides nice mathematical frameworks, they provide hardly viable solution.

Table 3.2: Supply Chain Finance — Network based

#	Article	Objective	Methodology
1	[61]	Design of combined financed scheme for banks based on loan-to-value rates (LTV), which express the ratio of a loan to the value of an asset purchased	Numerical simulation
2	[54]	Analysis of the influence of the core company on the supply chain through "energy diffusion" model	Numerical simulation

3.5 If Supply Chain Finance Fails

SCF initiatives are one of the best strategy to reduce the cost of capital, but unfortunately not always the underlying conditions for its application are satisfied. Specifically, we will refer to a mathematical framework of SCF [84] to better understand these conditions. The model is well representative of the general framework of the most widespread SCF initiatives [20]. For a more detailed list, *see Appendix A*. A SCF initiative depends on several variables:

- P is the project about to be financed.
- t is the time horizon for the financing of P.
- r_{project} is the expected return of the *target company*[3] from the project about to be financed.
- i_{target} and i_{partner} are respectively the borrowing cost respectively of target and partner[4] entity
- $p \in [0; 1]$ is level of information asymmetry of the partner company regarding P. Let 1 be absence of asymmetries.
- C is the cost to eliminate all the information asimmetries
- $r_{\text{partner}} = r_{\text{target}} \times p$ is the expected return for the partner company
- y are the extra benefits the partner company expect from the success of the project of the target company. As an example:
  - Image benefit

[3] The company object of the SCF.
[4] The company collaborating in the SCF project.

- Strategic information by the help of P
- Influence on P and the rights connected to it
- Synergies or diversification from other financed projects
- Strategic benefit arising with from the contractual framework governing the right to access P

Let $\boldsymbol{sc}$ be the array of all the companies in a given SC, i the array of borrowing rates for each and every the companies in $\boldsymbol{sc}$, r the requested return from a given project P, p the degree of information asymmetries of each entity with respect to P (i.e. the uncertainties related to the project P) and y the external benefit brought to a company upon realisation of P. A SCF initiative is realised only if $\exists\, sc_i \in \boldsymbol{sc}$ (i will be hereafter called *partner*) for which the following conditions are satisfied:

c.1 $r_{partner} \times p + y \geq i_{partner}$

c.2 $r_{partner} \leq i_{\text{target}}$

Should there be more than one potential partners, the SCF program will be undertaken with the partner for which the difference $i_{\text{target}} - r_{partner}$ is maximised. The condition c.1 represents the incentive for the partner company to finance the project. Specifically, the financing can happen if the expected returns on the financing of the project for the partner entity plus its expected external benefits are higher than the cost of borrowing capital from an external financial provider. The condition c.2 reflects the incentive of the target company to join the SCF program: this will be convenient only if the expected return from the potential partner are not higher than the target's current borrowing rates from the bank. If both c.1 and c.2 are satisfied, there is a bipartisan incentive to undertake the SCF initiative. Should one of these fail, there is no option for the SCF.

Notice that, for several SCF initiatives, there is a direct involvement of the financial institution in the deal, that is, the partner company does not actually borrow money and lend them forward to the target corporation, but, more easily, the latter can borrow at a reduced rate thanks to the intermediation of the partner. Still, this does not change the mathematical structure of the model.

Also, it is noteworthy to remind that this framework does not require the partner company to be necessarily more financially reliable than the target company, nevertheless, since the impact of the positive external benefit y is likely harder to quantify in a satisfactory fashion, this condition hardly applies.

It turns out there are three major instances where the aforementioned conditions do not hold, as the model assumes different conditions that could be easily not be satisfied. In first place, the partner company might have an alternative investment yielding r_{ext} such that: $r_{partner} \times p + y < r_{\text{ext}}$. Secondly, according to the model, the investment for P is assumed marginal with respect to the size of the partner entity, so that this would not influence the risk of the partner company. Should this not be true, $i_{partner}$ would increase making harder the fulfilment of condition c.1. Eventually, the degree of information asymmetries might be too high for the partner to bare the risk of the financing ($p \to 0$) and, contextually, the cost for additional information higher than the marginal benefit to the whole project due to a reduction of the return requested by the partner (i.e. whenever $\Delta p \times C > || \frac{d}{dp} r_{partner}|_{p0} ||$, see 3.1[5]).

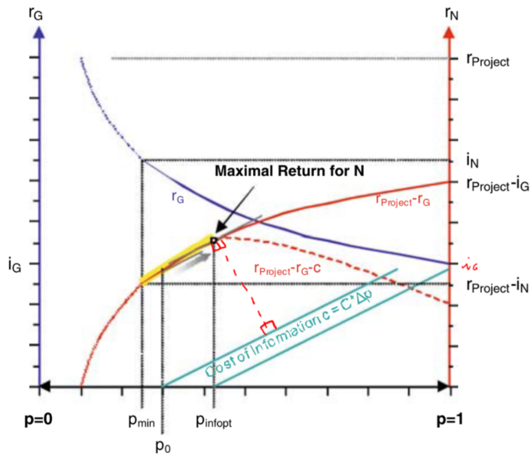


Figure 3.1: SCF — Theoretical equilibrium point

Indeed, because of the mentioned issues, most of the SCF initiatives are usually promoted by big players in the SC, so-called anchors [71]: large corporation with a central role in the SC. These organisations are characterized by lower borrowing costs and they can rely on consistent SC information related to the projects to be funded, as they usually rely on powerful SCM-IT systems. This implies that, in absence of multi-tiered supply chain initiatives, the distance from an anchor directly influences the likelihood of being eligible for SCF decreases (i.e. the chance that $\nexists\ sc_i \in \mathbf{sc}$ alias that c.1 and c.2 increase). This is due to the assumption that, the more dispersed in the SC a company is, p decreases, the cost of information soar and the external benefit y are even harder to quantify. The same results have been determined through numerical simulation in a recent study on SCF and the impact of the network [61].

What has been presented above, might reflect the situation of a SME that does not operate close to a SC partner and interfaces directly only with other similar-sized small organisations.

In an attempt to econometrically describe a measure of integration (or vice versa, the degree of dispersion) of a corporation in a supply chain let us introduce the monotonically increasing function $I(r(p), p, y; P)$. Given a project P, issued by the target company, the higher the requested returns by potential partners, or the higher the information asymmetries, or the lower the perceived external benefit, the less likely is P to be funded through SCF. Should I be too low to trigger SCF, the target company can hardly rely on SCF and needs to bare its own borrowing rate i_{target}. This is clearly an issue as it reasonable to expect the less integrated firms to be rather small and thus with a quite significant borrowing rate, thus leading to a vicious loop to the detriment of the weakest players.

[5]N is the target company, G is the partner company

Chapter 4

Basel Regulatory Framework

In this section the current regulatory framework for capital adequacy – and consequently, the basics requirements for credit risk assessment – will be deepened. The rationale is in the need of understanding of how credit institutions should handle the issue of credit risk assessment. The matter would deserve more than these few pages to be exhaustively discussed and the current section will analyse the issue as far as SMEs credit risk is concerned.

Basel Accords are three sets of banking regulations (Basel I, II and III) set by the Basel Committee on Banking Supervision (BCBS): the standard setter for the prudential regulation cooperation on banking supervisory matters, whose mandate is to strengthen the regulation, supervision and practices of banks worldwide with the purpose of enhancing financial stability [45]. One among the different purposes of Basel Accords, is to set rules to ensure that financial institutions can have enough capital on account to meet obligations and absorb unexpected losses arising from their businesses. Different risk categories are defined, among which: Market Risk, Credit Risk, Operational Risk, Business Risk, Real Estate Risk. Specifically, Credit Risk is the extent to which extreme fluctuations in credit exposures could impact the bank. Credit Risk arises from nonperforming/defaulting exposures, such as bank loans.

The overall amount of money financial institutions are required to keep aside is often called Regulatory Capital (RC) or capital adequacy/requirement.

4.1 Early Approaches

The governing framework of Basel I [6] did not consider the peculiar risk of obligors, in favour of a 4-classes repartition,[1] depending on the typology of the financial asset to be assessed, *see Appendix B*. Therefore, RC was calculated as:

$$\mathrm{RC} = \mathrm{RWA} \times \mathrm{CAR}$$

where:

1. RWA is the risk weighted capital, i.e. the real weight of an exposure given the risk of default of said exposure. RWA = A × RW.

    (a) A = Size of the exposure

[1] Five, if considered asset given no rating.

   (b) RW = Risk weight [0; 1]. It is a proxy of the default risk of said exposure

2. CAR (Capital Adequacy Ratio) = Fixed threshold (≥ 0.08). Percentage of RWA to be held in the regulatory capital.

4.2 Recent Developments

This static approach brought naturally two antipodal issues: excessive and insufficient capital coverages. This is because the regulatory capital could not adequately reflect the peculiar risk of the single financial asset. The issue has been tackled in Basel II [7], with the introduction of a dynamic risk appraisal procedure.[2] Specifically, under Pillar I,[3] two main procedures are now allowed:

1. Standardized Approach (SA)

2. Internal Rating-Based (IRB) approach

   (a) Foundation-IRB (FIRB)

   (b) Advanced-IRB (AIRB)

The underlying principles remains those of the prior document and the formula for capital requirement unchanged even if the risk weighted assets can be now calculated in different ways.

In the SA, sixteen different typologies of claims are specified, each of them associated with a specific risk weight which may now vary way over 100% of the value of the claim itself. With this approach, bank can take the help of external rating agencies for the appraisal of the credit weights. SA is not really a substantial improvement with respect to the former model, maintaining a good share of the prior issues.

On the contrary, within the IRB, the bank itself personally takes part in the definition of the weights. Under this approach, banks must categorize their exposures in five classes (*see Appendix B*). For this work, we will make exclusive reference to corporate exposures, with specific focus to the sub-categories of project finance, object finance and commodities finance. Basel regulatory framework provides a general, parametric model for whatever class of exposure that banks should fill with its own estimation of the risk parameters. The risk weight of a single exposure is now (*see Appendix B*) defined as :

$$\mathrm{RWA} = \frac{f(\mathrm{PD}, \mathrm{LDG}(\rho), \mathrm{EAD}, \mathrm{M})}{\mathrm{CAR}}$$

where:

- PD = probability of default of an obligor: $\max(0.03\%; \mathrm{PD}_{1y})$

- LGD = Loss given default: loss rate on a specific exposure in an event of default.;

[2] In its essence left unchanged by Basel III [9]

[3] Basel II is articulated in three macro sections (Pillar I, II, III). Pillar I deals with maintenance of regulatory capital calculated for three major components of risk that a bank faces, operational, market and, for this work purposes, credit risk.

- EAD = Exposure at default: estimation of the extent to which a bank may be exposed to a counterparty in the event of, and at the time of, that counterparty's default. It is the equivalent of what the size of the exposure (A) was for Basel I;
- M = Effective maturity: expected maturity of the loan. The shorter, the less risks underlying credit risk of the exposure;
- CAR = same as for Basel I
- ρ = Regulatory defined parameter to account for the alleged correlation of the exposures of the financial asset in lenders' portfolios. This is one of the strongest assumptions of the model. The matter will be discussed more in detail in the next sections.

Main difference from 2a and 2b is the option, for banks adopting the AIRB approach, to calculate their own estimate for PD, LGD, EAD and M, while institution adopting FIRB can only provide assessment for PD, needing a regulatory assessment for the other parameters.

IRB main strength points, with respect of the former model are:

1. Improvement of risk sensitivity: capital requirements based on internal estimates are more sensitive to the credit risk in the bank's portfolio of assets.
2. Leverage on incentive compatibility: banks should be encouraged in adopting better risk management techniques to control the credit risk in their portfolio to minimize regulatory capital.

4.3 Portfolio-Invariance Assumptions

The universality[4] of this model is guaranteed [49] under the assumption of portfolio-invariance, that is the fact that the capital required to add a single exposure to a portfolio depends uniquely on the obligor's attribute and, by any means, on the portfolio characteristics. This property holds under two fundamental assumptions:

1. The portfolio must be asymptotically fine-grained, meaning that the largest exposure cannot account more than an arbitrarily small share of the total portfolio exposure. In the reality, this condition adequately satisfied in portfolios accounting more than a thousand exposures.
2. There must be at most a single systematic risk factor across obligors, i.e. the correlation ρ in credit events is due to the common dependence to a unique systematic factor. It is a rather strong assumption since, in the real world, the economic cycle is a composite of a multiplicity of cycles tied to geography and prices of production input. In fact, it is universally recognised that a single-systematic factor model cannot reflect the impact of small scale events that, even if they do not affect the whole portfolio, can strongly affect the default rate of a regional subset of obligors. This is especially true for SMEs, for which local economic cycles have

[4]Validity across different asset classs and portfolios, thus permitting its implementation worldwide regardless of the peculiarities of a given bank portfolio

a stronger influence. However, since markets do not provide precise information on correlations of credit events across obligors yet, and for the need of generality, the IRB model could only have been developed in this way.

4.4 Correlation Coefficient and Supporting Factor

With reference to SMEs correlation with the systematic factor, it has been shown [36] that the dependence on the economic cycle is significantly lower in case of SMEs, therefore in the assessment in the calculation of Risk Weighted Asset (RWA), smaller firms benefit from a reduction in the calculation of ρ, proportional to each SME turnover. Given a set PD, the maximum improvement achievable is 0.04 percentage points (*see Appendix B*). In addition, since beginning 2014, SMEs benefit from the so-called Supporting Factor (SF),[5] set to reduce the capital requirement for SMEs and thus to ease the access to credit, as the bank would need to keep less capital for SMEs exposure. Specifically:

$$\mathrm{RW}_{\mathrm{SME}} = \mathrm{RW} \times \mathrm{SF}_{\mathrm{SME}}$$

At any rate, no evidence of the impact of the supporting factor has been yet observed [36]. This clearly suggest that a decrease in the cost of capital for smaller borrower could only arise from an improvement in the PD estimation process.

4.5 Rating System Design

As the work aims – as stated in the introductory chapter – in providing a novel methodology for the estimation of SMEs creditworthiness, it is important to review and be aware of the accepted standards to provide an applicable solution, rather than merely a theoretical result.

Basel accords details the framework of an accepted rating system for IRB purposes. The rating system is defined as the set of methods, processes, control, data sources and IT systems supporting the assessment of credit worthiness/credit risk. It is noteworthy to recall that the same institution may have customized rating system for specific industries/market segments. That is crucial given that the aim of the new model will be to best describe the peculiarities of SMEs.

4.6 Rating Dimensions

As mentioned in the introduction, a qualifying IRB rating system must have two separate and distinct dimensions:

1. The risk of borrower default. This dimension must aim exclusively in assessing the default likelihood of a borrower (PD).

2. Transaction specific factors, such as collateral type or seniority of the exposure. (Though this work will not cover this issue).

[5] Introduced to counterbalance the increased capital requirements. It is currently 0.7619.

4.7 Probability of Default and Default Rate

Basel II framework [7], suggest three non-binding approaches. Whatever the methodology, the chosen one must be clearly justified to the supervisory authority:

1. Internal default experience: grades derived by a proprietary model (Pooled data from other institution are allowed);

2. Mapping to external data: associating internal grades to the scale used by an external rating institution or similar institution and then attribute the default rate observed for the external institution grade to the banking corporation grade. The external institution criteria must be oriented to the borrower risk and not reflect the nature of the specific transaction.

3. Statistical default estimation method: a simple average of the default probability estimates for individual borrower in a given grade

Overall, there are two main sources from where a bank can draw the estimation of the default likelihood: the internal (proprietary model) and external credit assessment institution (authorized credit rating agencies). A brief excursus on these realities is done in the following section.

Smaller SMEs exposures [7] are very often pooled in clusters, by region, industry and size, of which the historical default rate $\frac{\text{Obligors defaulted in the period [t-1;t]}}{\text{Obligors at the end of the period t-1}}$ is calculated and assumed as the expected default rate in the calculation of the capital requirements. The threshold discriminating obligors treated as single name (i.e. individually) or pooled together, is normally proportional not to the size, rather to the exposure that the bank has with each obligor. Despite PD is still calculated at the level of the individual obligor, the access to credit of the pooled entity is influenced by the clusterization process. That is to say, a pooled entity might experience restrained access to capital because the pooling procedure does not reflect its actual creditworthiness, thus mistakenly assigning an excessively high risk while the obligor which is indeed worth a loan.

Overall, to clarify the difference: PD refers to the single name obligor and represent the probability of default over a given period, while the default rate is the maximum likelihood estimator of the mean of the distribution of default within a given asset class. This raises the question of bottom-up and top-down approaches [51] which will be made furtherly explicit later on.

4.8 External Credit Assessment Institutions

ECAIs, also known as Credit Rating Agency (CRAs), are companies whose business is to assess (and sell) credit ratings of other institutions and to their securities. It is crucial to understand this difference as there exist two different typologies of rating. The first is the rating of the obligor (i.e. the creditworthiness of the company): an opinion on the default likelihood of an entity, that is the extent to which such institution will be able to repay all its liabilities. The second category is the rating of the obligation: a judgement on the riskiness of a specific financial instrument issued by an obligor,[6] i.e. the extent to

[6]For instance, a corporate bond

which a generic investor will be able to get its money back: the less likely, the higher will the premium required by an investor be. More in detail, the European Securities and Market Authority (ESMA) classifies the different type of rating as follow [43].

Table 4.1: Rating types

Obligor ratings	**Obligation ratings**
Corporate ratings	Covered Bonds
Sovereign and public finance	Structured finance

For what concern obligors, within the category corporate ratings, we find the credit opinions concerning financial, insurance and non-financial corporations, ranging from large multinational to smaller businesses. In the sovereign and public finance category fall credit risk assessment of national entities and public entities. The corporate ratings category might also include unsecured bond rating, while sovereign and public finance shall include the treasury bonds. Despite being financial instrument, these particular kinds of obligations closely reflects the absolute creditworthiness of the issuer and thus they can be considered as such, in absence of a specific obligor rating [83].

Under the obligation ratings category are classified covered bonds, financial instruments usually issued by publicly traded corporation, and structured finance. The latter is a set of complex financial instruments. Within each sub category, rating methodologies might strongly differ, according to the peculiarities of the evaluated entity (either corporation or asset).

To certain extents, the credit risk of an issue is function of the creditworthiness of the issuer. For instance, the rating of the covered bonds is directly related to the creditworthiness of the issuer, of the rating of an asset base security, directly depends from the quality and the correlation of the assets in the security. Ratings can be either short or long term. Conventionally, long term rating assesses creditworthiness along a time horizon longer than one year. A formal definition of credit rating has been already provided in the introductory chapter.

A further distinction needs to be made between solicited and unsolicited ratings. The first are ratings expressly requested by an obligor, while the latter are usually demanded by a third party (most likely a bank, for IRB purposed) or not requested at all.[7]

All the credit risk obligation ratings are – by their nature - solicited, as they have to be requested by the institution who wants to issue a security, while not all the creditworthiness rating are solicited. The percentage of solicited/unsolicited rating emitted changes for every CRA considered, but the tendency is towards solicited rating [38]. For both solicited and unsolicited creditworthiness rating, the emission is, at least in a first phase, in confidential form. In the latter case, the involved company is informed as well.

ECAIs market is highly concentrated, with the three biggest companies accounting for more than the 90 percent of the total revenues. Although new firms have entered the European credit rating market - which currently consists of 26 registered and 4 certified credit rating agencies - most of the smaller CRAs rate a limited set of asset classes and

[7] The incentives leading CRAs to issue non-requested non-solicited rating is still today a subject of debate among scholars.

have limited cross-border activities and geographical scope [41]. For the extended list, *see Appendix C.*

As mentioned, for the scope of this work, we will be interested solely by obligor ratings, i.e. the PD parameter required by the IRB model. Specifically, the focus will be on corporate ratings in the sub-category of small and mid-sized enterprises.

4.9 Rating Structure

A banking corporation must have a meaningful distribution of exposures across grades, with no excessive concentration on a specific grade, both on the borrower rating scale than in the exposure/facility rating one. To fulfil this purpose, a bank must have a minimum of seven borrower grades for non-defaulted borrowers and one for those that have defaulted. The Supervisor might require a more detailed borrower grading scale, to avoid excessive concentration of borrower in a given grade which might be a proxy of the model not being able to accurately differentiate borrowers risk. Should the eventuality take place anyway, a bank institution must be able to adequately justify the similarity of creditworthiness for borrowers that band. The borrower scale is a bucketed ranking of borrowers PD, for which each borrower is assigned a given rating according to the risk interval it falls into.

Borrowers must have their ratings updated at least on an annual basis, but the frequency of the revision of the rating must be adequately increased according to the riskiness of the borrower. Therefore, banking corporation must have an effective process to obtain and update relevant and material information on one borrower's financial condition, as well as a procedure to update quickly a borrower's rating.

The trade-off between need for up-to-date ratings and comprehensive evaluation of the borrowers stems from the non-optimal information collection process of banks, and it is one of the biggest issues for credit rating.

4.10 Rating Criteria

A corporation must have clear cut rating definition, processes and criteria, so that the rating assessment would be uniform across departments and different geographic locations. The detail of the rating instruction must be sufficient to allow an external auditor to understand the assignment of rating. As a general principle, information used to determine the rating must be current: the less information a banking corporation has, the more conservative its assignment of exposures to borrowers must be. This is a huge problem for smaller corporations. Also, even though an external rating can be the primary factor in determining an internal rating assignment, each institution must ensure to consider other relevant parameters, when needed. Criteria for a qualifying credit risk assessment are: [69]

- *Understandability.* Clear definition of the conditions for which a model works. The parameters driving a particular assessment should be clear and intuitive as well.

- *Predictive power.* A model that is unable to differentiate between good and bad companies, is clearly of little use in credit decisions. A consequence of a powerful tool is the willingness of experienced personnel to use it in pricing and decision making.

- *Default-oriented.* The model must be calibrated to probabilities of default (PDs), i.e. yield values $\in [0;1]$. While even an uncalibrated model can be used to decline or accept credits, it is of little use in ensuring that any risk assumed is accurately priced and capitalized. Furthermore, it will be of little use for trading debt. Thus, a benchmark must be tied directly to probability measures through empirical calibration.

- *Validated.* It must be Empirically validated. Without documented performance on large datasets, prudence dictates that a third-party model must be viewed sceptically. Such testing also gives the user confidence that the model is stable and has not been overfitted.[8]

The way information is used to build the model is crucial in determining the capability and robustness of the final model in predicting default. Some factors will be useful to predict default, but others are likely to be spuriously related to the default variable. Some of them take extremely high or low values for some companies, without adding any information for default prediction purposes. Given the large number of possible factors, it is important to reduce the list of ratios that enter the final model selection process, according to the aforementioned principles.

Eventually, in spite of the one-year time horizon used in PD estimation is one year, as previously highlighted, banking corporation are expected to use a longer time horizon in the forecasting process.

4.11 Use of Models

Despite being useful to avoid biases typical of models in which human judgement plays a large role, statistical or mechanical rating procedures necessarily use only a subset of available information, leading to other sources of imprecision in the creditworthiness/credit risk assessment. This is the reason for which human oversight is anyhow necessary to ensure that all relevant and material information outside the scope of whatever model, are somehow taken into consideration. This process is called *override* or *notching*. Though, if the resort to external adjustments is too frequent, the model needs to be revised as it is clearly not efficient [93].

[8] Usually overfitting happens when a model is built and tested on a single sample, resulting in a very good estimator for that specific sample, due to the inclusion of a high number of non-significant regressors. Such models are worthless are they usually perform badly on other samples. The extreme situation of model fitting is represented by point interpolation.

Chapter 5

Credit Risk Assessment

The process of evaluation of a borrower's creditworthiness falls within the vast realm of risk management. In its more general conception, risk is defined as the effect of uncertainties on objectives[1] [63], has been historically analysed by scholars from several perspectives. Specifically, the subject of credit risk assessment is rather relevant represent approximately the 10 percent of scholars' production in the business field.[2]

Whatever entity in charge to assess the probability of default of a company, they must face the tough challenge of commensurating the qualitative differences of a heterogeneous set of borrowers into a unique quantitative difference [22] on a graded scale describing the likelihood that they will be able to meet their objective, (i.e. the full repayment of its obligation in the amounts and in the times settled). Under the perspective of agency theory, credit risk assessment must be performed in presence of hidden information (i.e. without the same level of knowledge of the borrower herself regarding her business) and in an efficient manner (i.e. in a fashion for which the costs involved in going beyond information asymmetries would not overwhelm the expected benefits from a given exposure[3]), but that could anyhow, at the same time, guarantee to the lender a reasonable coverage from moral hazard risks.

5.1 Two Main Approaches

As for the standard risk management discipline, it is important to distinguish among two different approaches: top-down and bottom-up. For credit risk assessment purposes, the top-down approach is generally applied to – allegedly homogeneous – portfolios of smaller exposures. The method looks at the macroeconomic situation and at the historical default data, and through distributional assumptions related to both the factors, infer the default likelihood of the companies in said portfolio, according to the degree of correlation of the entities with the macroeconomic factors. As mentioned earlier, top-down approach is employed to assess the risk of the smallest, yet most numerous, exposures. Conversely, the bottom-up (alias look-through) approach overlooks the economic conditions while

[1] Objectives may assume various facets (such as financial, health and safety, and environmental goals) and can apply at different levels (such as strategic, organization-wide, project, product and process).

[2] 10.08 percent. (2,794 papers tagged *rating* OR *default* out of 25,960 articles tagged risk management in the categories Business, Management and Accounting and Economics, Econometrics and Finance) Source: https://www.scopus.com

[3] In essence, net cash flows from interest repayment

focusing on the individual attributes of the rated entity.

Both approaches have advantages and drawbacks. The top-down approach, thanks to distributional assumption, allows a simplification of the problem, in that it does not consider micro interactions and only focuses on the macro-level effect. If this approach is very efficient in terms of the lower level of required information and computational power,[4] it is also strongly affected by the distributional assumptions and it is not able to quantify the effect of the complex interaction at the entity-level. As mentioned, one of the core assumption of the IRB framework is the dependence of PD of the loan portfolio from a unique macroeconomic factor [49], though it is widely recognised this assumption to be rather unrealistic, especially when it comes to the SMEs world.

Instead, the bottom-up philosophy tries to overcome the liabilities of the opposite approach through the effort of modelling and appraising the micro-level interaction of the rated entity. As predictable, the bottom-up approach entails a higher level of complexity with respect the top-down, therefore being often affected to the issue of data availability. Also, even bottom-up models might neglect some important aspect from either the micro and the macro environment. In practice, CRAs and banks uses combinations of the approaches according to the situation and to their information availability.

Studies [51] comparing the two approaches with respect to their ability to predict loss distributions correctly have shown that the top-down approach can underestimate the true risk measures for lower investment grade issuers. This generates a vicious circle, as lower grade investments are very often small enterprises, which are always clustered for the mentioned reasons.

5.2 CRAs and Rating Factors

Financial institutions are not required to publicly disclose their mathematical models for the creditworthiness assessment. Likewise, the same applies to the external rating assessment institutions, provided that, as for the banks, the reliability of their procedure is periodically assessed by an external auditor.

Even if models and methods to assess the rating are undisclosed, external credit rating agancies must compulsorily divulgate the determinants (or factors) and part of the procedures involved in their credit risk appraisal process [94].

It is possible to categorize the determinants under two dimensions: the first, denotes the structure of the data itself: quantitative and qualitative, the second dimension describe data's nature: financial or non-financial. By their nature, the all financial data falls into the quantitative category. Such data are accounting figures and ratios. On the other hand, non-financial information can be differently structured. For instance, the strategic plan and the structure of the organisation or the external economic conditions are unstructured types of information, whereas the operational variables will have a more structured shape. Each of these data contributes differently to the building of a credit rating. Common practice wants the quantitative information to represent the backbone of any rating estimation and they usually feed a statistical model, whose outcome is eventually complemented and refined by the judgement of one or multiple analysts in a

[4] Indeed, generally, credit risk assessment the computational requirements need processor architectures to be able to handle large amount of data

process called override, which lead to the definition and the approval of the final rating. Table 5.1 presents a summary of the factors, categorized by nature.

Table 5.1: Rating factors

Financial	Non-financial
	Macroeconomic conditions
	Competitiveness
Profitability	Strategy
Capital structure	Corporate governance
Quantitative financial analysis	Value chain
Financial ratios	Technology and R&D
Liquidity	Other operational aspects
	Risk
	Group impact

For a more detail overview on the sub-categorisation of these factors, *see Appendix D*. Not surprisingly, financial indicators account, on average, for the 90 percent of the final rating [80]. Qualitative and quantitative information leads to different biases in the rating process:

- Statistical model based on financial data relies on the implicit assumption, that to a similar financial/operational structure should correspond a comparable default likelihood. Numerous models, among which [2], [4] and [3]) have been developed to take into account different peculiarities different types of companies. Nonetheless, none of them succeeds in providing perfect PD estimations, nor guarantees the control of outliers. Most importantly, it is plagued by backwardness, meaning that financial figures, are not fully representative of the up-to-date condition of an enterprises.

  Other pitfalls concerning the use of financial data, reside in the assumption that the reporting framework are shared[5] and, most of all, that financial data are available at all, condition not necessarily true for a huge number of non-publicly traded companies, especially if SMEs. Anyway, the claim that such models could be fully representative of a company risk is at least hazardous.

- Non-financial, qualitative data have the merit to allow analyst to better address the outcome of a statistical quantitative-based model, yet this capability presents the main drawbacks of being subject to the idiosyncratic biases of the human error, hardly predictable or avoidable. Another issue arises complementarily to the first one: any mathematical model built to overcome human judgement, struggle in identifying the statistical relevance of a given variable and the predictive capabilities are hardly applicable to more than a limited number of cases. This, is due to the theoretically infinite panorama of non-financial variables that may feed these models and to the fact that those are very often specific of a very small subset of organisations. In addition, these models carry on all the conceptual issues highlighted for the previous point.

[5] Which, by the way, considering the diffusion of IFRS and the GAAP seems to be quite a reasonable assumption. In any case, CRAs adjustments to financial statement somehow mild the issue

5.3 General Description of CRAs' Rating Process

As far as ratings of the issuers are concerned – regardless from being solicited or not – the corporate rating process usually follows seven main steps:

1. Request of a credit assessment by an issuer company or by a third part entity. Valuation of the feasibility[6] and signature of the contract.
2. Collection of information, both publicly available and confidential. Meetings with the client.
3. Generation of a preliminary rating and internal assessment of the final profile among the designated team of analysts.
4. Private communication of the rating to the interested parties
5. Appeal window. The interested parties might raise their concerns regarding the procedure of the analyst team and in case, provide evidence of this and/or additional relevant information that may have been previously neglected. Possible (seldom) reiteration of 2 3 and 4.
6. Rating disclosure. The rating is uploaded on the company's database. It is now available (It must generally be purchased).
7. Monitoring and periodical assessment of the rating. The review usually take places every year or when the ECAI observe some non-negligible events potentially hampering the solvency likelihood of the rated entity.

Also, as already mentioned, CRAs might provide different models for what concerns 3, mostly depending to the industry in which the rated company works. This is necessary as the parameters take into consideration for the evaluation of the company and their weights differ. It is not the purpose of this work to list the rating methodologies of the different ECAIs, but still, here following are exemplified a couple of the most common practices for explanatory purposes, as, despite the methodologies may be different, the underlying principles are equivalent.

5.4 Standard & Poor's Methodology

With reference to step 3 in the rating process, figure 5.1 shows the approach of Standard & Poor's. The company detains the 40 percent of the EU market share.

The process is articulated in two phases. The initial stage involves the determination of the anchor, i.e. a baseline reflecting the key characteristics of the rated firms, which is then updated according some further qualitative information, named modifiers, regarding the company and its environment. The anchor is simply a weighted average of the financial and of the business profile of the rated company. The financial profile reflects the degree of leverage of the company and it is calculated from two core indicators:

- Cash Flow To Debt Ratio $= \frac{\text{Operating Cash Flow}}{\text{Debt}}$

[6] Respect of minimum requirements in term of current condition of the company and availability of the information.

- Net Debt to EBITDA = $\frac{\text{Debt}}{\text{EBITDA}}$.

The first one, cash based, indicates how much of the net debt a company could pay back is covered from the cash flow from operating activities (or how many times in one year a company can pay it back). The second, accrual based, indicates how many years would it take to the rated company to pay back its total debt back with the current performance. From different perspectives, both the indicators express the leverage degree of a given company.[7] The business profile, on the other hand, reflects three non-financial risk dimensions of the evaluated company: country risk, industry risk and competitive position. Simplistically, we might say, respectively: PESTEL, Porter's 5 Forces and SWOT analysis. As already mentioned, the company risk dimension is quite often neglected when assessing SMEs business profile, due to the lack of information.

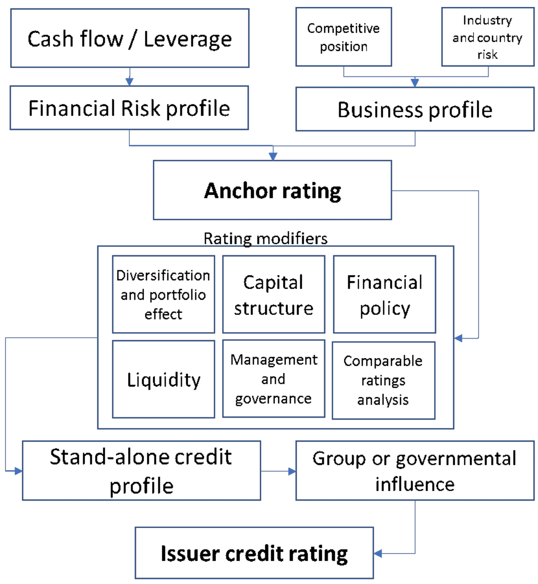


Figure 5.1: S&P methodology flowchart

Once the anchor has been set, S&P analyst's team apply modifications to the rating of the company through an additional set of information regarding:

- Diversification and portfolio effect: the impact on the PD of the different businesses of the company. This hardly applies to SME due to their single-business-focus nature;

- Capital structure: how the focal firm finances its operations, i.e. considerations regarding the debt-to-equity ratio;

- Financial policy: policies related to the regulation, supervision, and oversight of the financial and payment systems, including markets and institutions, with the aim to provide financial stability, market efficiency and asset and customer protection.[8] Again, this does not really apply to smaller business and it could be sometimes hard to assess;

- Liquidity: indicators of cash availability;

- Management/Governance: self-explanatory, though the causal correlation with the riskiness of the enterprises is questionable, especially for SMEs and once again, the governance difficult to assess, where formal roles and responsibilities might not reflect the relevant decision makers; [9]

[7]They are not proper leverage ratio, but S&P use them as a proxy for the leverage.
[8]Source: OECD https://stats.oecd.org/glossary/detail.asp?ID=4469
[9]Think about family-owned businesses

- Comparable ratings analysis: self-explanatory, though difficult it might be difficult to find effective comparable for smaller businesses, due to the lack of data and possibly the absence of an public and/or updated rating for said comparable.

The output of this phase is defined stand-alone credit profile: a semi-definitive rating, that is finally assessed according the impact of the group or governmental influences, i.e. a qualitative factor measuring the extent to which the solvency risk of the rated company is influenced by the arbitrary deliberations a third party, either an influence group or a governmental measure. Once this last assessment is completed, the definitive issuer rating can undergo the scrutiny of the rated company in the appeal window. It is quite clear how a number of parameters considered does not really fit with the extremely variegated world of SMEs, thus potentially leaving unexplained part of the crucial characteristics of the focal company. This, in turn, reflects on the rated company itself, as the uncertainties in the rating process translates in lower rating grades.

5.5 Moody's Methodology

Analogously to S&P approach, Moody's methodology (the second biggest player in CRAs market) focuses on the both financial and non-financial performances. The company discloses its rating methodologies for different categories of companies for a number of industries.

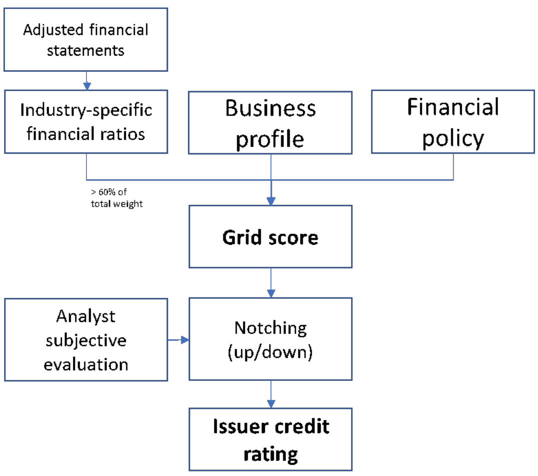


Figure 5.2: Moody's methodology flowchart

The rating processes are different industriwise. For non-financial corporations, the company initially defines list of critical factors for the specific industry. Said factors may have different structure and nature, financial or non financial, quantitative or qualitative. As a reference, we provide two examples in table 5.2. Each factor is described by one or more sub-factors. To each sub factors a weight is assigned. The analysts calculate the value of all the quantitative factors and define qualitative judgements on the quantitative ones. Each sub-factor is then ranked according to Moody's scale (Aaa to C). All the sub-factors are then transposed to a numerical grid and a weighted average is then calculated according to each grid. Moody's final rating is inferred through transposing back the final score to the number-rating conversion table.

Table 5.2: Moody's industry weight factors

Retail	**Oil and Gas**
1. Scale [10%] (a) Revenue 2. Business profile [30%] (a) Stability of Product (b) Execution and Competitive Position 3. Leverage and Coverage [45%] (a) $\frac{\text{EBIT}}{\text{Interest Expense}}$ (b) $\frac{\text{Retained Cash Flow}}{\text{Net Debt}}$ (c) $\frac{\text{Debt}}{\text{EBITDA}}$ 4. Financial policy [15%]	1. Scale [25%] (a) Average daily production $[\frac{\text{mboe}}{day}]$ (b) Proved reserves [mmboe] (c) Crude distillation $[\frac{\text{mbbls}}{\text{day}}]$ 2. Business position [20%] 3. Profitability and Returns [10%] (a) $\frac{\text{EBIT}}{\text{Average Book Capitalisation}}$ (b) $\frac{\text{Downstream EBIT}}{\text{Total throughput barrels}}\ [\frac{\$}{\text{bbl}}]$ 4. Financial policy [20%] 5. Leverage and coverage [25%] (a) $\frac{\text{EBIT}}{\text{Interest Expense}}$ (b) $\frac{\text{Retained Cash Flows}}{\text{Net debt}}$ (c) $\frac{\text{Debt}}{\text{Book Capitalisation}}$

5.6 SMEs Credit Rating Among CRAs

The approaches illustrated so far, apply mainly to big public corporations. The discipline of credit rating for SMEs is indeed rather underdeveloped. Among ESMA authorized CRAs, Cerved Ratings and ICAP Group are reported to be mostly focused on small businesses [43]. As a reference, in the EU panorama, less than one CRA every three advertise tailored solutions for SMEs.[10] For further details, *see Appendix C.*

A couple of reasons might be argued to this regard. The first one, is that historically,[11] the sole purpose of ratings was for investors to evaluate the risk for speculative purposes [21]. Since most SMEs are not publicly traded nor they issue corporate debt, there was no much interest into having a rating for them assessed. The second reason, more practical, is that it is extremely difficult to categorize such peculiar realities under comprehensive framework the same way it is done with bigger entities. Data collection and integrity continues to be an issue for the smallest entities [29]. It is not a coincidence that the biggest Italian CRAs: Cerved Ratings and Crif Ratings, turn out to be branches of Italy's biggest information provider for business corporations (Cerved and Crif). Same reasoning for Axesor in Spain. Likewise, in Germany, Euler Hermes is member of Allianz

[10]and ICAP Group is not among those.
[11]Early '1900

Group, a leading global financial integrated financial service provider and GBB-Ratings was born under the umbrella of the Auditing Association of German Banks.

SMEs credit rating has started becoming of any interest once banks had the necessity to somehow proxy the creditworthiness of their smaller borrowers to comply to regulatory capital requirements, but is for the most part remained a prerogative of banks' internal rating systems. Another reason for which various rating agencies, despite not having a dedicated product for small and medium enterprises, developed tools to estimate creditworthiness of SMEs was to provide credit risk assessments for structured finance products, especially for CLOs. Notice that in this specific case, SMEs PD evaluations do not affect the access to finance of the given SMEs, but an analysis of the assessment criteria might however reveal some interesting approaches.

Table 5.3: SME-related ratings

Corporate rating *Advertising or reporting rating procedures developed explicitly for SME*	**Structured finance rating** *Advertising or reporting SMEs rating s part of the rating securitisations process, especially CLOs and ABSs*
Axesor S.A.	ARC Ratings S.A.
CERVED Group S.p.A.	DBRS Rating Limited
CRIF S.p.A.	Creditreform Rating AG
Euler Hermer Rating GmbH	Fitch Group
GBB-Rating Gesellschaft für	Moody's Group
Bonitätsbeurteilung GmbH	Scope Credit Rating GmbH
ICAP Group	Standard & Poor's Group
Cumulated market share as for December 2015	
2.16%	*96.17%*

Overall, as shown in table 5.3 the entire knowledge about credit rating agencies approaches for SMEs could be the categorized under these two distinct categories.

Despite claims, is a matter of fact how only few of the abovementioned companies effectively put some efforts in building a specific model for SMEs. Within the structured finance category, only Moody's provide a framework for the small businesses, while the other CRAs rely on top-down statistical model that does not really tackle the issue of the assessment of the individual creditworthiness. Similarly, on the corporate rating-side Axesor, CRIF Ratings and Euler Hermes Rating, do not publish any specific methodology for SMEs. Cerved Ratings releases rating for small businesses but apparently does not have a dedicated approach. The same reasoning for ICAP group, which by the way, proposes a dedicated procedure for companies that do not publish financial data. Eventually, GBB-Ratings, despite publishing a model for SMEs rating, it is only focused on financial corporation ratings. Also, even amongst SMEs-dedicated approaches, it does not seem to emerge a real breakthrough, a significantly different approach. Rather, it looks like these models mostly mimic, on a smaller scale, the approaches adopted for bigger corporations.

Following, we briefly list the most insightful approaches for both categories. For a more details on all the mentioned companies, *see Appendix E* and *F*.

5.7 Moody's Analytic RiskCalc

Before presenting the model, it is necessary to introduce Moody's approach to rating SME balance sheet securitisation regulation: a framework to assess credit risk of a bank whit exposures in a pool (or portfolio) of SMEs. Particularly, when said portfolio is not granular, i.e. when there are exposures relevantly sizeable with respect of the overall pool, and/or when the historical data are not sufficient to model the risk of the bank portfolio with a distributional approximation, the framework require the estimation of the individual SMEs' probability of default.

As most of the SMEs' in a bank portfolio are unlikely to already have a rating from an external credit assessment institution, the analyst will look either at the one-year PD internal estimates from the bank itself or, more interestingly, will apply the Moody Analytic RiskCalc, a proprietary tool to asses an unpublished point-in-time opinion of the credit quality of an issuer,[12] for which no credit ratings exist. The latest version of said model is, for obvious reasons, not publicly available, though, looking at an older declassified document [69], it is possible to establish the model being a probit model. The model discussed in said paper was developed for the country of Singapore, but it can give a glance of what is the approach of the Company. It is fed by six factors. For each of them, the authors considered the ratios that had better discriminating power on a sample test of firm:

- *Profitability.* Proxied by $\frac{\text{Net Worth}}{\text{Total Interest Expenses}}$ and $\frac{\text{Operating Profit}}{\text{Total Assets}}$. As expected, the higher the profitability, the lower the default risk. Notably, the two mentioned indicators proved to be the most reliable in terms of discriminating power.

- *Capital Structure.* Proxied by $\frac{\text{Total Liabilities} - \text{Cash and Marketable Securities}}{\text{Total Assets}}$ and $\frac{\text{Retained Earnings}}{\text{Current Liabilities}}$. The first ratio is an important indicator of a company's financial stability because the more of the liabilities that cannot be covered by liquid assets (expressed as a percentage of total assets) the worse the company will fare in a downturn. Similarly, retained earnings expressed as a fraction of current liabilities can be thought as a proxy for the cushion the company will have in downturn.

- *Liquidity.* Proxied by $\frac{\text{Cash and Marketable Securities}}{\text{Total Assets}}$. This reflect the tendency for companies with lower current ratio and smaller holdings of cash to have higher default probabilities

- *Activity.* Proxied by $\frac{\text{Current Liabilities}}{\text{Net Sales}}$.

- *Growth.* The dynamic of growth variable is rather interesting. In fact, the growth-to-PD curve is u-shaped, meaning that to excessively high growth rates correspond both successes and failures. Growth is proxied by $\frac{\text{Liabilities}}{\text{Net Worth Growth}}$.

- *Size.* Proxied by real total asset. The higher, the lower the probability of default.

Different linear combinations of variables are then fed to a probit model and the tested against different samples with different ratio of defaulting companies. The test aims to assess the accuracy ratio of the model, i.e. $\frac{\text{Defaulted companies in the sample}}{\text{Model-predicted defaults}}$. The closer the

[12]But also of a security or a financial contract.

ratio is to 1, the more accurate the model is. If the ratio is higher than 1, the model overestimate the default likelihood of the sample, vice versa, PD is underestimated. The resulting best performing model gave high relevance to profitability and size indicators.

Specifically, the weight of the covariates are:

Table 5.4: Moody's Analitic RiskCalc variables

Variable	**Weight**
Profitability	26%
Capital Structure	24%
Size	14%
Growth	13%
Liquidity	13%
Activity	10%

5.8 Cerved Rating

Cerved Rating Agency is an Italian credit assessment company. They provide a suite of statistical model to evaluate the creditworthiness. Their model is used to assess creditworthiness of SMEs as well. No detail information is disclosed regarding the models. Similarly to S&P approach, the rating process starts with the computation of a score, resulting from the combination of quantitative and qualitative information. Said score, is then assessed by an analyst to define the final rating [1].

Quantitative information includes:

- Data from financial statements
- Structural, macroeconomic, territorial and sector variables

Qualitative (behavioural) information includes:

- Data from a public source, such as negative events involving the company, its shareholders and the related companies
- Proprietary information, such as details on the regularity of payments taken from Payline. [13]

Interesting to notice that the company is trying to integrate the payment data in the rating procedure and, in general, tries to include in the rating process a behavioural factor, reflecting the current trend of the rated entity, in an effort to temper the scarce promptness of traditional source of data.

5.9 ICAP Group

As said, no specific SME-specific methodology is published. Anyway, according to the general methodology, whenever there is the need to amend to the lack of financial

[13] Payline is a proprietary platform that integrates payment data of more than 2 million of Italian SMEs.

information, the company relies on derogatory data. Derogatory data are information on an entity credit report that can be legally used to turn down a loan application; they includes late payments, charge-offs and bankruptcies. Particularly, they focus on the analysis of commercial and sales data. The company operates in the receivable management business as well, thus it is likely they can leverage on several delinquency information regarding their clients, to assess their rating.

5.10 GBB-Rating Gesellschaft Für Bonitätsbeurteilung GmbH

GBB-Rating has developed a rating procedure specifically for German-resident small and medium-sized enterprises. The procedure gives particular consideration to the industry-specific particularities of production. Particularly, the rating process is subdivided in two different assessment: financial profile and business profile.

The financial profile is assessed with a logit regression on quantitative financial information from the financial statement. Pooled data from multiple years are considered, and the outcome of the logistic regression is adjusted according to previous years' trend. The business profile is evaluated by analysing mainly qualitative and forward-looking external and internal influencing factors. Said factors are related to the market, the organisation and the general risk profile of the company. The assessed attributes are integrated according to a defined standard, which can be adjusted for business model particularities. No indication regarding the proxies for business evaluation are provided.

5.11 Other Perspectives: CRISIL SMEs Rating

Held by S&P, this India-based rating agency is specialised in the rating of SMEs. The company has a long tradition in the rating of SMEs in India in close partnership with the Indian government, that subsidizes the fees for the rating up to 75 percent.[14] CRISIL assesses the sustainability of a business plan and a firm's long-term viability by studying the track record of the business, the profiles of customers, the relationships with customers and suppliers, and level of infrastructure and technology in the business [26]. Specifically, the overall creditworthiness depends on two core components, as shown in table 5.5 financial strength and operating performances, the latter categorized as business or management risk. In order to assess an SME's business risks, information regarding business plans and growth strategies are collected directly from the entity. Typically, SMEs are a part of the value chain of larger industries and are usually not in direct contact with the end-users, thus, assessing the quality of the relationship with its key customers is critical. To assess manufacturing facilities, a site visit by analysts or business associates is often performed. Also, key suppliers are contacted to assess the quality of their relationships with the SME being rated. Eventually, the combination of the strengths of said parameters is plotted on an eight-level rating grid, specifically designed to compare SMEs creditworthiness. Though, no mentions to probability of default are provided.

[14] http://www.crisil.com/ratings/nsic-crisil-credit-rating-scheme.html

Table 5.5: CRISIL SME rating

Financial Strength	**Business Performances**
	Business Risk
• Accounting quality, transparency • Disclosure of financial statements • Financial Flexibility • Debt protection matrix • Working capital management • Financial risk analysis • Assessment of sales and net worth Business risk	• Track record of the business • Customer profile • Relationships with customers and suppliers • Planning and growth • Quality of facilities
	Management Risk
	• Promoter competence • Integration with customers • Succession plan • Aggressiveness

5.12 Incentives

There is evidence to believe that SMEs credit rating is rather neglected by CRAs because of the absence of incentives. Indeed, the business model of CRAs [21] is either subscription-based[15] or issuer-pays.[16] As the process for credit rating is very expensive, there is no reason for CRAs to undertake SMEs rating market, since price tags might be prohibitive for small businesses and very likely there would not even be external investors to break-even a subscription plan. No surprise that the two main businesses for CRAs are big corporate ratings, for which not having a credit assessment from one (if not more) reputable institution generate a negative feeling among investors and obligations rating, as every traded security requires a rating and financial markets are flooded with securities.

As for December 2015, there are 24,889 long or short-term corporate rating[17] outstanding[18] against 40 thousand large corporation and more than 200 thousand mid-sized firms.[19] The figure refers to corporate issuers that do not belong to insurances or financial institutions. The total, including these categories, is 28,316. Although it

[15] Rating is not disclosed, investors pays access to the rating of an issue/issuer and periodical fee is required to receive updates to the rating.

[16] Once defined, the rating is public and it is entirely paid by the promoter of the rating initiative.

[17] For a detailed categorisation of the rating types, refer to (European Securities and Market Authority, 2016; Commission Delegated Regulation (EU) No 448/2012, 2012)

[18] CEREP database, limited to European countries and to Corporate issuers that do not belong to Insurances or Financial institutions. Including registered and certified CRAs rating. The value, at net of the certified CRAs is 24,512.

[19] [78]. 23 million firms, of which 92.8 percent micro, 6.0 percent small, 1 percent mid-cap, 0.2 percent large.

is not possible to tell exactly which percentage of these rating concerns SMEs, there is a clearly a huge imbalance in numbers, to the detriment of SMEs: it is likely that approximately 20 thousand ratings belong to small businesses, given that Cerved Ratings and ICAP Group are reported to have a customer base mostly represented by smaller corporations [20] [43] and they represent almost the 38 percent of the outstanding corporate ratings. For more details, *see Appendix C*.

5.13 General Description of Banks' Rating Process

Ultimately, in the vast majority of the cases, financial institutions are accountable for the creditworthiness estimation of their customers and, as mentioned, banks do not fully disclose their models. It is thus unclear to which extent their analysis of SMEs credit risk is pushed. If it is true that the biggest financial corporations adopt AIRB approach for large companies, it is also unclear to which extent they assess the creditworthiness of small businesses in the same way. In lot of cases, small businesses credit risk assessment seems to lay on the threshold for the application of top-down distributional-based approaches, where the PD of an entity strongly depend by exogenous parameters, neglecting the idiosyncratic factor. For more information on the disclosed procedures, *see Appendix G*. As a synthesis, it is possible to define two different approaches that are in general adopted by banks [46]:

- Relationship based. Banks assess the creditworthiness of their clients in the medium to long term and provide appropriate products, advice, services and assistance. This kind of relation generally generate soft, and typically proprietary, information about the borrower that is hard to verify by other parties and subjective by nature.
- Transaction/information based. Banks can exploit information synergies from their commercial activities. Their loan officers rely on information that is verifiable by third parties and is largely financial.

The choice of the approach, despite being subjected to some constraints and to periodic revision by the regulators, is ownership of the financial provider. SMEs' creditworthiness assessment models have a time horizon of typically one year and are usually based on four independent modules [65].

Table 5.6: Determinants of bank rating

#		*Data type*
1	Financial module	Accounting data
2	Internal behavioural model	Borrower's behaviour with the evaluating bank
3	External behavioural module	Borrower's behaviour with the banking system
4	Qualitative module	Qualitative judgement of the relationship

According to the availability of financial, behavioural and qualitative data, the model will incorporate all or just a subset of these modules. Module 1, 2 and 3 originates a score (probability of default), while module 4 is normally employed to correct up or

[20]Together they publish 20,852 long term rating for non-financial corporations.

downward the rating class corresponding to the default probability assigned either a. by financial and behavioural models, or, b. by the portfolio segment where the SMEs is located, in case information other module classes are not available.

Table 5.7: Example of a bank's rating scheme

Financial module	**Behavioural module**	**Qualitative module**
• $\frac{\text{Gross Margin}}{\text{Interest Expenses}}$ • $\frac{\text{Interest Expenses}}{\text{Turnover}}$ • $\frac{\text{Shareholders' Equity}}{\text{Total Assets}}$ • $\frac{\text{Total Debt}}{\text{Total assets}}$ • $\frac{\text{Cash}}{\text{Total Assets}}$ • $\frac{\text{Gross Margin}}{\text{Total Assets}}$ • $\frac{\text{Turnover}_t}{\text{Turnover}_{t-1}-1}$	• Internal – 6 months' average $\frac{\text{Outstanding Withdrawn}}{\text{Withdrawal Limit}}$ – 3 months' average unauthorized withdrawn • External – 6 months' average $\frac{\text{Outstanding Withdrawn}}{\text{Withdrawal Limit}}$ – 3 months' average unauthorized withdrawn	Example of questionnaire: • Age of the relationship of investment not linked to strategic company's business • Is there a business plan? It has been implemented? • Negative involvement in extraordinary operations • Dependence on key managers

The most commonly used statistical models to generate the score from financial and behavioural variables are logistic regression and discriminant analysis. Once the score has been defined, it is calibrated according to the internal long-term default experience of the correspondent asset class, to link the outcome of the statistical model to historical default data.

Table 5.8: SME rating in major EU banks

	HSBC Holding	BNP Paribas	Deutsche Bank	Credit Agricole	Barclays Plc	Societe Generale	Banco Santander	Groupe BPCE	RBS	Llyods Banking	UBS AG	Unicredit SpA	ING Group	Credit Suisse Group	BBVA
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
Dedicated SMEs model	x	x	x	x	x	x						x	x		x
External CRA assessment					x		x	x			x				
Financial module		x	x	Ns[21]		x	Ns	x	x	x	x	x	x	x	x
Behavioural module	x	x	x	Ns	x		Ns					x	x		
Qualitative module	x	x	x	Ns		x	Ns	x	x	x	x	x	x	x	x

[21]Not specified in the registration document

In table 5.8, an overview on the methodologies of the 15 biggest European banks by total asset. Information are presented as they are disclosed in banks registration document. Not all the entities declare specific dedicated models for SMEs, in which case they are categorized either as corporate or retail exposures.

5.14 SMEs Credit Risk Assessment In a French Bank

Practice slightly differ from theory. As an example of a of the combination of top-down and bottom-up approaches mentioned, here the methodology applied by a nondisclosed major French bank. SMEs represent approximately one third of the top line of the entity. The scoring grid in table 5.9 covers coverage, leverage and performance ratios plus other non-financial information, totalling seven factors and two warning signals. It was developed to target SMEs with a turnover in the range of € 30 million. For the detailed grid *see Appendix H*. All factors are equally weighted. Notably, beyond some conventional financial ratio, the model considers, industry trend, and managerial skills. The last non-financial parameter is the credit opinion of Bank of France:[22] a three-year creditworthiness assessment. It is questionable whether the managerial skill and the assessment of their quality, could truly be a significant discriminant for creditworthiness. Moreover, basing the evaluation on the BoF score would simply shift the problem on a different level, considered that the evaluation is mostly based on the same criteria [11].

Table 5.9: SME rating scheme of a French bank

Financial module	**Behavioural module**	**Qualitative module**
• $\frac{\text{Shareholders' Equity}}{\text{Total Assets}}$ • $\frac{\text{Total Net Debt}}{\text{EBITDA}}$ • $\frac{\text{Interest Expense}}{\text{EBITDA}}$ • $\frac{\text{Gross Profit}_t}{\text{Gross Profit}_{t-1}}$ • $\frac{\text{Total Net Debt}}{\text{Shareholders' Equity}}$ • $\frac{\text{EBT}_t}{\text{EBT}_{t-1}}$	–	*Relationship* • Managerial skills • Bank of France score *Others:* • Bank of France score

5.15 When Traditional Credit Rating Fails

There are three main reasons for which traditional financial-based rating systems experience difficulties in assessing small enterprises.

The first one has a very practical nature: due to their legal structure and according to legislations, SMEs might not be obliged to file their annual statement in the modes and times as required for publicly traded companies. Still, even if data are available, their

[22] Eleven-class scale.

figures might show extremely unusual structures, with respect to the standard fashion of bigger corporations. Therefore, a traditional approach might suffer both from the lack of the data required to be used and misbehave when the rated firm does not respect the standard of financial structure assumed by the model. Different approaches to counter this issue have been developed, mainly relying on joint data repository [29] [101] and/or on-line advanced information sharing techniques as blockchain [17] [85]. The idea of shared ledger, from a theoretical perspective, triggered the interest of some major EU banks, who are planning a platform to increase EU SMEs trade [5].

The second issue is the – at least questionable – belief that a firm must unconditionally resemble a pre-set financial structure in order to be deemed healthy and profitable. A reason for which financial ratio are widely used in credit risk assessment is that they allow to regress the default likelihood of multitude of different firms based on common parameters. This make sense, especially for large companies, as their financial figures are the aggregate of a huge amount of detail data and might assume more similar or, let's say, characteristics and expectable behaviours (for mathematical modelling purposes), being – given non-defaulting conditions – strongly correlated from a year to another. The same assumption is questionable for smaller businesses, whose financials are more affected by exogenous variables. As an example, the Cash Ratio $= \frac{\text{Net Income}}{\text{Total Assets}}$ of a corporation with thousands of transaction records and cost items and hundreds of million worth in fixed assets is more likely to be stable, under ordinary circumstances, than the same ratio for a SME with only a few hundred or less of recorded transaction and a couple of workshops in the countryside. Small variation in the factors of the ratio for the smaller company might lead to huge fluctuation of the appraisal, without necessarily indicating bad performance from said company. Financial structures of smaller enterprises are more typified and not always happen to mirror those of larger ones: for instance, higher working capital requirements or higher indebtedness are not always correlated with lower profitability [86]. If ignored, these effects might result into negatively-biased credit risk valuations and, thus, in higher interest rates and collateral requirements. In addition, based on financial data, traditional ratings do not adequately account for the influence of the business environment on a rated company and they are time-bounded to the date of the filing of a borrower's last report. This is perhaps not a big issue for bigger corporations, whose financial inertia[23] yields slower changes in profitability, but instead, it is crucial for small businesses which are easily subjected to year-to-year fluctuations [82]. It is a matter of fact that for smaller enterprises financial data really need to be read in function of the context and to the extent to which they can provide a realistic picture of the situation [61].

The third and last reason is that none of the applied approaches truly consider the importance and leverage on the interaction between enterprises: as mentioned, value chain factor are diluted in the 10 percent weight of non-financial factors. On one side, this may be of secondary importance for large corporations, as the impact of bad partners on the credit risk of a very large cash-rich firm is often negligible. On the other, the profitability of a small enterprises is highly influenced by the performance of the supply chain partners[24] [12]: relevant information on the performance of the enterprises that

[23] Due to the bigger numbers involved, highly-aggregated values compensate for smaller fluctuation in the disaggregated data.

[24] And to a certain extent, even from that of non-partners.

might be inferred from neighbouring firms [88] are often overlooked by the conventional approaches. Overall, this goes to the detriment of SMEs, who are inevitable penalized by rating criteria that are not tailored on their needs and do not manage to reflect their idiosyncrasies.

Chapter 6

Models in the Literature

Although the models remain mostly undisclosed, academic literature provides numerous examples. Here, we will present a classification of the most relevant [33]. Two main categories of statistical approaches are given: parametric and non-parametric. The main difference is that for parametric models, the vector of the parameter[1] θ is given and fixed, meaning that the behaviour of the model[2] does not change whatever the observed data D is. That is to say:

$$P(x|\theta, D) = P(x|\theta)$$

In other words, in parametric models, the complexity of the model is bounded, making them less flexible for more complex tasks. On the contrary, in a non-parametric model this assumption is released, so that the outcome of the model changes with D. The aim of the following sections is to give a flavour of both these approaches.

6.1 Definition of Statistical Model for Credit Rating

In its more general form, a statistical model for credit rating is a multivariate function

$$f : \mathbb{R}^n \to [0; 1]$$

that takes as input a vector x of n variables observed at a time $t_0 = t - L$ and return a value that reflects the probability of default of a borrower whose characteristics are listed in the vector x. The output can be binary or continuous in the interval $[0; 1]$, depending on the model considered. Regardless from the cardinality of the output, we will assume the output reflect the probability of default of the borrower, hence value closer to 1 will indicate higher PD, and vice versa.

Typically, there are two phases in the life of the model, in the first one, statisticians test the correlation of a selected variables with a set of organisation whose condition is known (either defaulted or non-defaulted), to assess the connection of such variables to the two conditions. The relevance, or explanatory power, of each variable can be assessed through various statistical techniques such stepwise regression [30] or principal component analysis [57]. In a second stance, the model is tested on a different sample of corporation, whose performance are also known. In the ideal situation, the process is

[1] The factors/determinants proper of the specific model.
[2] Probability assigned to x

reiterated until the model can foresee the default outcomes in the sample with an error rate lower than a requested threshold, that is, the probability that a company would be considered defaulting (or non-defaulting) when it is not is lower than a fixed percentage. Once the model has been tested it can be applied in the real world. $L = t - t_0$ is the time horizon of the model. Normally, the longer L is, the less accurate are the prediction of the model.

6.2 Regression Analysis

It is the classical and most simple approach. The model is

$$S = \boldsymbol{\beta}^{\mathrm{T}} \times x + \varepsilon$$

where $S : \mathbb{R}^n \to \mathbb{R}$: and ε is the non-explained variability. This model presents two main issues: first of all, the output (S, the score) is not bounded, therefore, whereas it can anyhow be employed for relative comparison of different entities, it does not generate a PD that can be compared with other estimation from different model. The second issue is that the coefficient $\boldsymbol{\beta}$, output of a Ordinary Least Square (OLS) reduction, is in fact biased, as the vector x of the variables is not homoscedastic, that is, the individual variables do not have the same variance. Approaching the estimation of $\boldsymbol{\beta}$ through a weighted less square reduction could mild the issue, but the estimator is still biased. Under certain conditions, the heteroscedasticity of the vector could be alleviated through a transformation of the sample data [15] but, still, this is not an issue that will be discussed in this work, nor it is reasonable to believe that a simple regression model, even when unbiased, could be able to explain the facets of more than a small subset of similar enterprises.

6.3 Discriminant Analysis

This technique has been used by since the early ‘60s by seminal works on the subject such as [2], [4] and [3]. The function is $S = \boldsymbol{\beta}^{\mathrm{T}} \times x$ where the coefficient vector is the result of an optimisation problem, being the optimal solution to that maximise of the variance between the groups of good and bad borrowers whilst minimizing the variability within the each group category. The optimal solution is proven to be a linear transformation of the $\boldsymbol{\beta}$ vector of the regression model. Therefore, the model has the same pros (overall, the simplicity), and, more importantly, carries all the biases and imperfection of its twin model. Mathematically speaking, if in the building of the regression model $\boldsymbol{\beta}$ is the outcome of an OLS, in the discriminant analysis it is the outcome of a stepwise regression.

6.4 Logit and Probit Models

These kinds of model are specifically designed to analyse binary dependent variables. Both models rely on a so-called latent variable, linked to borrower characteristics exactly as in the previous two models, but scaled of a coefficient u arbitrarily determined so that if the latent variable is greater than 0, the binary outcome assumes value 1 (default) and vice versa. To exemplify, let S be the latent function $S = \boldsymbol{\beta}^{\mathrm{T}} \times x + u$ and y the dichotomous variable so that

$$\begin{cases} 1 & \text{if } S > 0 \\ 0 & \text{otherwise} \end{cases}$$

this implies that, set zero as the threshold of the default set of event, it is then possible to determine the likelihood of a company to default, i.e. its PD. Let $F(\cdot)$ be the cumulative function of the random variable describing the failure of the enterprises, so that $P(y = 1)$ is realized when, under the assumption that such random variable is symmetric $P(\boldsymbol{\beta}^{\mathrm{T}} \times x + u > 0) \Rightarrow P(u > -\boldsymbol{\beta}^{\mathrm{T}} \times x) \Rightarrow 1 - F(-\boldsymbol{\beta}^{\mathrm{T}} \times x) \Rightarrow F(\boldsymbol{\beta}^{\mathrm{T}} \times x)$ At this point, the choice of the abovementioned random variable, albeit symmetric, is purely arbitrary. In case $u \sim \mathcal{N}$, we will be in presence of a probit model, if, of the contrary, u is assumed distributed as a logistic distribution, then we will have a logit model. Back in times, the preference of the logit towards, the probit was dictated by computational necessities, but today, the two approaches are equivalent.

- Normal distribution:
  - Density $f(\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x}|\mu, \sigma^2) = \left(2\sigma^2\pi\right)^{-\frac{1}{2}} \exp -\frac{(\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x} - \mu)^2}{2\sigma}$
  - Cumulative $F(\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x}|\mu, \sigma^2) = \left(2\pi\right)^{-\frac{1}{2}} \int_{-\infty}^{\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x}} \exp \frac{t^2}{2} dt$
- Logistic distribution
  - Density $f(\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x}|\mu, \sigma^2) = \exp \frac{\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x} - \mu}{s} \left[s\left(1 + \exp \frac{\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x} - \mu}{s}\right)\right]^{-1}$
  - Cumulative $F(\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x}|\mu, \sigma^2) = \left[1 + \exp \frac{\boldsymbol{\beta}^{\mathrm{T}} \cdot \mathbf{x} - \mu}{s}\right]^{-1}$

The problem of the heteroscedasticity of the vector $\boldsymbol{\beta}$ persist, though. Two key advantages comparing with the earlier approaches is that the outcome of a probit/logit can be interpreted directly as the probability of default of a given borrower, and, moreover, the statistical relevance of the model and of the vector $\boldsymbol{\beta}$ can be more accurately determined.

6.5 Panel Models

Until now, all the models considered were cross-sectional, meaning the covariates x were related to the same period. Typically, banks possess the value of these covariates on a longer time span. The possibility to give time deepness to a model, expanding the cross-sectional data to a panel dataset, improves the stability and, to a certain extent, the precision of the model. Panel models allows the model to include in the model macroeconomics factors, or to model the life cycle of the asset, de facto shifting from a point-in-time to a through the cycle assessment. This is particularly useful considered that those kind of data, differently from financial ratios,[3] are up-to-date, which may turn out to be useful to perform borrowers' stress tests. As for their structure, panel models can be be the underlying function of standard logit/probit models. In the estimation of the vector $\boldsymbol{\beta}$ must be accounted the possible correlation between the same covariates along multiple years. If cross-sectional data normally satisfy this requirement, panel data does not, thus potentially generating overfitting.

[3] Which are very often two years old when used for risk assessment [33].

6.6 Hazard Models

All the previous model describes the PD of a borrower within a given time frame. Anyway, they do not provide any information regarding the likelihood of future default of borrowers who should not default within the set period. Hazard model tries to tackle this issue considering a survival function, i.e. the probability for a non-defaulted borrower to default at any given time t in the future. The most general model [25], does not make any assumption on the hazard function, $h_0(t)$, also called the baseline hazard. It can be written as: $h(t|x) = h_0(t) \exp \boldsymbol{\beta}^{\mathrm{T}} x$ The baseline hazard can be interpreted as the average PD of the company sample at a given time t. This value gets multiplied by a coefficient accounting for the covariates of the individual borrower. Let $\boldsymbol{\beta}^T x = 0$ be the coefficient for the average borrower, the higher this will be, the higher the PD, and vice versa. Two main drawbacks arise from this kind of approach: the first is that the model assumes the default as a continuous variable while in the reality the conditions of a company are measured discretely; the second is that, at least in this formulation, the model supposes the covariates unchanged in time, which is an unrealistic event. Thus, the main drawback of this category of model is related to the fact that it is not straightforward to build model that could solve the mentioned issue, defining more realistic assumption. On the contrary, it might be useful to be able to calculate the likelihood of default at any given period of time.

A common application of hazard models is to infer credit risk from the analysis of Credit Default Swap (CDS). Starting from the expected PD in on a given time frame, the model allows to calculate the conditioned PD in future periods. This, by the way, implicitly implies the need to have previous PD estimation outstanding. Hence, the approach is most suitable for companies with a liquid CDS market and thus is not appropriate for small business. At any rate, the outcomes for the model do not usually guarantee good accuracies.

6.7 Decision Trees

This and the following model presented are a step forward in the practice of risk modelling. All the approaches presented presuppose that the parameters of the model[4] θ are independent from the set of observed data[5] D, hence $PD = P(x|\theta, D) = P(x|\theta)$.

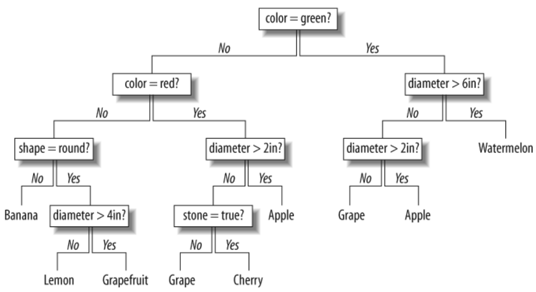


Figure 6.1: Example of decision tree

Non-parametric models release this assumption, so that $\theta = f(D)$. The explanatory power of the model, i.e. the amount of information that θ can capture about the data depends also on the cardinality of D, that is, the more data, the more accurate the model can be.

Decision/classification trees consist in a series of conditional yes/no clauses, based on the vector of covariates, to classify borrowers in groups. Taking as an

[4]The vector $\boldsymbol{\beta}$ from previous model
[5]I.e. the length of the covariates vector x

example a binary classification tree, such as in figure 6.1, each node divides the set of borrowers into two different subsets until the end node is reached.

At the end of the process, the borrowers are subdivided into many classes, to which must be assigned a PD. This is also the main drawback of this approach, which is not assigning an individual score to the single borrower, thus not allowing to discriminate between borrowers within the same category. A minor downside, due to the fact that the model is not based on any statistical assumption, consist in the fact that it is not possible to assess the stability of a framework with statistical relevance. Robustness[6] is therefore linked with the goodness of the training sample. The model helps to frame potentially complex or nonlinear relationship among the variables: for instance a covariate might be become relevant only at a certain node of the tree and for a specific subset of borrower only. The ability to clearly model interactions among covariates, it is a further strength of decision trees, which unfortunately turn out to be particularly useful if the interaction between variables are somehow known a priori.

6.8 Neural Networks

Neural networks are named after the fact that they naïvely appear to simulate the way the brain works. A more formal definition of neural network is Multilayer Perceptron. A perceptron (see figure 6.2) is the elementary unit of the system constituted by n axons and a node which represent, respectively, n weights and one elementary operation, which takes the inputs and results the output of the operation of the weighted inputs. The value output from each node is "filtered", via a smoothing function, that rescale[7] the output so that the result do not diverge across multiple layers becoming too heavy for a processing unit.

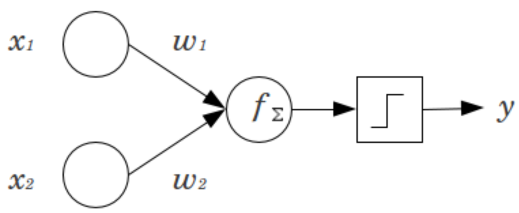


Figure 6.2: Trivial example of perceptron

In fact, they can be described by a series of concatenate matrix multiplications of multiple vectors of covariates x. The output of the model can be referred as the PD, related to the input through a series of intermediate nodes in layers (a concatenate series of perceptrons), who receives in input either the vector x or the output of other nodes and that, in turn, output a value to one or more downstream nodes or to the final output. No preliminary assumption is made on the structure of the intra-network relationships. Indeed, from its initial state, the network can be "trained" with different samples of defaulted/non-defaulted companies. Basically, the training is an iterative process called backpropagation, through which an algorithm asses the optimal weight of the nodes connection comparing the outcome of the current state of the network

[6]The ability to perform well on the new samples

[7]Diverse type of smoothing function have been described by literature. Primordial examples are the logit function ($f : \mathbb{R} \to [0; 1]$ as detailed above), or the tangent function $f : \mathbb{R} \to [-1; 1]$. Both function rescale the output to a limited interval. Recent development of the neural networks theories proven other, simpler function (Rectified Linear Unit aka $ReLU = \max(0, x)$), to improve the learning capability of the net.

itself with an expected output resulting from a fixed input. [8] The training continues until a satisfactory outcome is reached, which usually is an arbitrary error threshold, or predefined number of iteration of the feedforwarding-backpropagation procedure. Occasionally, a decay[9] function might be added to the network, to reduce overfitting to the training sample. The undisputed advantage of a neural network model is that it allows to model complex and previously unknown relationships between the input variables and the output. This is proven by the universal theorem of approximation [56], which proves that for any continuous function f on a compact set K, there exists a feedforward[10] neural network, having only a single hidden layer, which uniformly approximates f to an arbitrary $\varepsilon > 0$ on K. This capability is further extended to non-linear relationships if the smoothing functions applied at the end of each node is non-linear. The relationships are represented by the vector θ. Also, the model can be trained relatively quickly to adapt to new information, i.e. to changes in θ or in D. The last advantage, with respect to parametric models, is that, again, a multilayer perceptron does not require any distributional assumption on the data, a feature that extend its field of applicability. Another benefit of neural networks is that they easily allow to categorize the output in along $n > 2$ dimension, de facto being particularly suited for multiclass categorisation, as creditworthiness assesment, at is finest, is.

On the backside, the model is a at times similar black box in that it might be difficult to assess whether the relationships among the nodes are truly representative of the reality, which could lead a not enough robust model to behave unpredictably under particular conditions.

Overall, the approach is mostly suited to model situation where there is not a clear idea about the exact relationship among the variables. Different architectures of neural networks, different from the multilayer perceptron and allows to characterize different aspect of the inputs, for instance, their temporal relationship.[11] An in-depth analysis of nnets is outside of the scope of this work, for further reference to the topology, please refer to [96].

6.9 Statistical Model and Basel Requirements

Basel requirements for models have been discussed in the previous sections. Briefly to recap the most important:

1. Minimum of 7 classes for non-defaulted borrowers
2. No unjustified excessive concentration of borrower in the same class
3. Meaningful differentiation of risk among classes

[8]Historically, gradient descent was the most used. Again, as for smoothing functions, improvements brought newer and more performing algorithms (e.g. the Adam optimizer) that guarantee a better learning of the network, mainly, algorithmically changing the learning rate to speed up the convergence to the n-dimensional optimisation problem which backpropagation is, towards the global minimum of the cost function. A critical task is avoiding local minima and plateauing of the cost function.

[9]The decay function randomly "turn off" some nodes, thus forcing the backpropagation function to retrain the network. De facto, the decay function reset to zero the weights of some axes in the multilayer perceptron. This may sometimes improve the learning capability of the network by casually drifting from local minima in the optimisation function.

[10]wherein connections between the units do not form a cycle.

[11]See RNN, recurrent neural network

4. A plausible, intuitive and current input data

5. All relevant information must be considered

All the overviewed model could theoretically satisfy at said requirements.

Indeed, in principle, Basel's regulatory framework do not hinder any of these approaches, nor prevents an institution to employ an alternative solution with a solid theoretical foundation, that might have not been covered above. According to its peculiar strengths and weaknesses each model can fulfil more easily one or another requirement. For instance, regression and discriminant analysis models, despite having a plausible and intuitive input data, may suffer from the scarce timeliness of financial covariates and struggle in allow a distinction in classes of the borrower since the output of a standard regression are not bounded, which is an issue solved by the logit/probit approaches, which still lack from the perspective of the point 4 for the timeliness of the data. This issue is tackled by panel and hazard models, that sometimes may struggle on the statistical relevance of their assumptions. Non-parametric models are very strong in 5, but they might struggle at 3.

Chapter 7

Improving Credit Rating Through the Network

A recent survey of European CRAs [74] defined twenty-four sub-factors from the value chain that are incorporated, to different extents, in the rating assessment. These determinants aim at analysing structures, processes and performances of the SC and how their impacts on the business performance of the rated entity, but their final impact on the grade is rather low.

Indeed, neglecting the supply chain perspective is a huge drawback of the traditional credit risk approach. A comprehensive assessment of SMEs performance should consider that each enterprise in the SC contributes differently to the creation of value and that financial indicators as the efficiency of capital turnover or cash flows, strongly changes among small enterprises according to their junctions with the surrounding environment [61].

7.1 Credit Chain and Bankruptcy Propagation

Looking at the SC network of an enterprise is of crucial importance. In a highly-tangled network of trade credits, the performances of the neighbouring nodes can strongly influence the rated company, since financial difficulties of a firm will likely affect SC partners. If we consider the event of bankruptcy - the ultimate stage of a defaulting corporation - as the instance for which a company is no longer able to repay its debt, we might argue that detecting early signals and degree of dependence from companies at risk, might be useful for assessing, in turn, the risk of the rated company. The rationale is that, the safer is the environment in which an organisation operates, the lower is the risk of a domino effect of these contingencies. Under this perspective, value chain factors might play a crucial role from a predictive perspective.

With regards to the SC network, we distinguish two different sources of bankruptcy [12]. The first kind is triggered by unexpected sudden increase of cost or decrease in revenue, i.e. when revenues become too low with respect of costs. The second one, occurs when a supplier at a certain level, is repeatedly not paid by one or more of its buyers. Said supplier, whose solvency capability has been hampered, could it turn not be able to pay its own suppliers, thus potentially triggering an avalanche of consecutive bankruptcies.

It is worthwhile to remark that avalanche bankruptcies might be triggered by financial institution as well which [28], in reaction to a first-type bankruptcy event, might restrain the access to credit to neighbouring enterprises that, in turn, following increased financing cost, will then go bankrupt triggering a vicious cycle effect.

The potential co-responsibility in the destiny of its borrowers, even more clearly re-state the importance for a lending institution to clearly assess the true risk of the SC network of its borrowers' portfolio.

One of the most interesting contribution of the paper, as mentioned in the headline of this section, is the modelling of the propagation of the bankruptcies. Considering the SC network as an oriented graph,[1] like in figure 7.1,an avalanche of events, that is a set of correlated event originated by the same source, might propagate either downward (a) or upward (b) along the chain. Because the nodes can generate both upwards and downwards phenomena, the avalanche of events can even propagate horizontally in the SC network (c, d), i.e. between nodes that, according to the oriented graph, it is not possible to relate following the simple physical flow of money. One of the core finding of the paper is that the allocation strategy of a firm, directly influence its performances, meaning that companies with a bigger and more reliable supplier outperformed those who had a more homogeneous set of upstream partners.

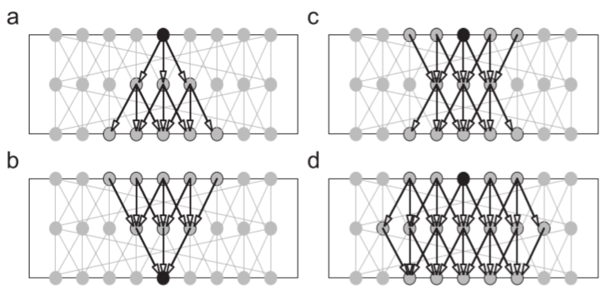


Figure 7.1: Bankruptcy propagation dynamics

The study provides an econometric framework to assess the probability of default of a company in the network. Here following, we will briefly discuss the matter. Suppose that the economy is composed by N firms organised in M production levels and let $i \in [1; N]$ be a generic firm and $K \in [1; M]$ a generic level in the network, with $K = 1$ the most upstream level and $K = M$ the retail level. Each firm at a given level K receives orders and provide supplies to a finite subset in the level $K+1$. Likewise the same company purchases from a given subset of companies in the upstream level $K-1$. A linear technology is assumed, i.e. the output of a given firm i at a level K will be defined by a linear transformation of the output of the supplier at the lever $K-1$:

$$Y_i^K = \sum_{j \in S_i} Q_{ij}^{K-1} Y_j^{K-1}$$

where S_i is the subset of supplier of the firm i at the level $K-1$ and Q_{ij}^{K-1} is the fraction of the total production of the supplier j at the level $K-1$ that is sold to the buyer i at level K, so that

$$\sum_{i \in K} Q_{ij}^{K-1} = \forall j \in K-1$$

. This formulation allows to describe the relationships between any production level. In

[1] Where the orientation defines the direction of the production flow.

matrix notation, $\mathbf{Y}^K = \mathbf{Q}^{K-1}\mathbf{Y}^{K-1} = \mathbf{Q}^{K-1} \times \cdots \times \mathbf{Q}^{K-J}\mathbf{Y}^{K-J}$, where J is the j^{th} level upstream from K.[2] The model evolves in time. Time is discrete and it is divided in periods of length t. At the beginning of each period, the firms at the level M sense the market demand and define their desired output, according to their production capacity. The demand from level M will be transferred to the companies at level $M-1$ and so on until level 1, so each company will define its production level for the given period t. Each company has a production capacity which is proportional with a factor $\theta > 0$ to its net worth $A(t)$, increases, from an initial endowment, of an amount equal to the net operational profit at every period t. Specifically,

$$A_i^K(t+1) = A_i^K(t) \times (1-\rho) + \pi_i^K(t)$$

where ρ is the depreciation rate per each period t, and

$$\pi_i^K = u_i^K(t)Y_i^K(t) - C_i^K(t)$$

is the profit for the period t. u_i and C_i^K are, respectively, the price and the cost relative to the firm i. Specifically, costs are calculated as $C_i^K = \sum_{j \in S_i} u_i^{K-1} Q_{ij}^{K-1} Y_j^{K-1}$. $\theta A(t), \forall t$ is the optimal amount of production to maximise the expected profit, i.e. the increase net worth at period $t+1$ i.e. $\max(A(t+1) - A(t))$. Since the optimal capacity of a firm might exceed or not be sufficient to cover the downstream demand, the planned output is set to be:

$$Y_i^K = \max\left\{\theta A(t); \sum_{j \in B_i} O_{ij}^{K+1} Y_j^{K+1}\right\}$$

where B_i is the subset of buyers at level $K+1$ of the firm i at level K and O_{ij}^{K+1} is the fraction of the total orders of a customer j at the level $K+1$ purchases from the buyer i at level K, so that

$$\sum_{j \in K} O_{ij}^{K+1} = 1, \forall j \in K+1$$

.

The term expected output is set by the minimum value between the expected demand and by the capacity constraints. The model introduces a failure function:

$$\begin{cases} 1 & \text{with probability } (1-q) \\ 0 & \text{with probability } q \end{cases}$$

and it represent the likelihood of a production failure. At the end of each period t, each firm might realize not to be able to fulfil its expected output, with probability q. This implies the fact that the company will not receive any revenue from its sales, but will still need to pay its customers for the supply of the materials, suffering a loss corresponding to $C_i(t)$. In case of failure, downstream firms would be affected in term of a reduction of their output of an extent proportional to the supply required from the supplier i that has not been delivered. Precisely, the losses incurred by a downstream buyer j of the supplier i amounts to $(u_j - u_i)O_{ij}^{K+1}Y_j^{K+1}$, i.e. the marginal revenue due to the supply

[2] Subject to the condition $K - J \geq 1$.

of i.

According to the amount of losses, a firm might default or not. A firm is deemed defaulted when the ratio $\frac{\text{Profit}}{\text{Net Worth}}$ is lower than fixed, negative threshold $-\beta$. That is to say, given $pi_i(t)$ and $A_i(t)$ respectively profit and net worth of the firm i at the period t, if: $frac\pi_i A_i < -\beta$, the firm is declared bankrupt. Assumed $\pi_i = u_i Y_i - C_i$, where u_i, the price of the good, is a random variable with probability distribution ϕ_i, we can define the probability of bankruptcy as

$$P\left(\frac{\pi_i}{A_i} < -\beta\right) = P\left(\frac{u_i Y_i - C_i}{A_i} < -\beta\right) = P\left(u_i < \frac{-\beta A_i + C_i}{Y_i}\right) = \int_L^{\frac{-\beta A_i + C_i}{Y_i}} \phi_i du$$

.

Mathematically speaking, L correspond to the ratio $\frac{-\beta A_i + C_i}{Y_i}$ of a firm with PD $= 0$. In fact, it is reasonable to assume the distribution ϕ_i of the price u to have, at least, a lower bound, coherently with the idea that there cannot exist prices lower than zero.[3] Such lower bound is nothing more than an artefact dictated by the need to have a baseline to be able to calculate the probability of default of non-riskless firms. The probability of bankruptcy increases if the net worth or the produced quantity decreases, as well as whenever costs increase. Even though indirectly, the model allows to calculate at each period the influence of another firm in the network on the probability of default of the rated company.

Here following we will focus on some innovative SC-based approaches and factors that under a SME perspective might allow the improvement of credit risk assessment.

7.2 Operational Performances

With this term, we refer to the metrics to assess the supply performance of a company: punctuality, timeliness, promptness, product/service quality, flexibility and conformity to customer requirements [64]. These variables are tracked by the vendor rating of downstream partner. According to the aforementioned survey on CRAs, it seems that external credit assessment institutions merely consider these parameters. They might be sometimes categorized as value chain sub-factors under the denomination of distribution sub-factors. [4]

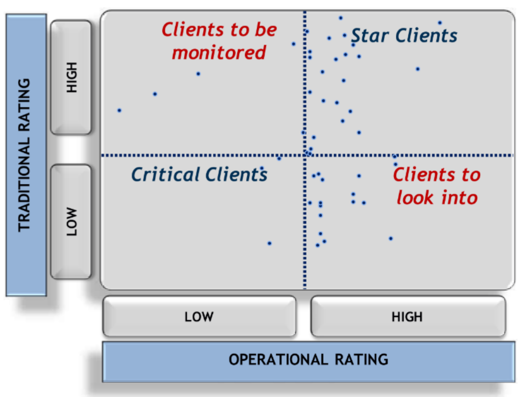


Figure 7.2: Integrated rating

At a first glance, they might not seem very relevant sub-factors, but especially for SMEs, they proved to be extremely reliant parameters to foresee the trend of the credit rating of SMEs on the medium term. A recent study [80], has retroactively proven the effectiveness of this approach on a small sample of enterprises.

Results have proven the capability of operational rating to anticipate trend of financial rating assessments. Comparing

[3]More reasonably, in the short run, prices must not be lower than the average variable costs
[4]Defined as parameters to describe the efficiency of the distribution network.

traditional and academic rating on a two-axis matrix, comparing traditional and operational ratings, the research showed that, misalignments between the two credit risk indicators were reliable warnings for the future performance of the company. The phenomenon was observed in both directions: over a 6-year time span,[5] companies with deteriorating operational performances and positive financial rating, showed a decreasing trend of the latter in the last period of the observation. The opposite trend was observed as well.

Still, the research had some limitations: the first related to the size of the sample, limited to 70 Italian companies, the second linked to the nature of the data collected. The researchers had access to aggregated only for what concerns the operational performances, meaning that they could not assess themselves the performance of the evaluated companies through analysing the operational variables, but they had to rely on buyers' evaluations. Vendors rating were very often inhomogeneous in term of both scale of evaluation and time of provision: some realities were assessed more frequently than others and the study group had to first rescale the heterogeneous vendor ratings and to take average values from the uneven sample they had available, eventualities that might have contributed to some biases in the evaluation.

The researchers themselves have highlighted these issues wishing for a uniform and impartial assessment of vendor rating data for a trustworthy evaluation and sharing of those performances. Indeed, the operational rating outcome of the model is not viable from the Basel perspective, in that it does not assign a punctual PD to the borrowers.

At any rate, it was not the objective of the study to provide a stand-alone creditworthiness assessment.[6] The major contribution of this research is the ability to show the link between operational performances and the trend of the credit rating assessment. Results have shown that, besides the actual implementation of the rating system, the possibility to have access to real time data on the operational performance of a given company might yield an improved credit risk model.

7.3 Data-Backed Approaches To SCF Credit Risk Management

We will now briefly introduce some innovative approaches, in table 7.1, to the SCF risk monitoring from the literature. The rationale is that the reduction of uncertainties can allow to better discriminate the real credit risk of corporation, through a reduction of information asymmetries[7] ($p \to 1$) and thus easing the access of good borrowers to SCF initiatives ([73].

These studies have tried to leverage big dataset for credit risk assessment. The information usually is provided from big data repositories and researchers try to look at detail data to infer general creditworthiness evaluation of the enterprises.

As noticeable, all the data sources are provided by banks or financial-related institutions. The models show how a credit rating scheme for SMEs could be developed when we do not have access to all financial ratios and only have data on lending from banks to SMEs.

[5] 2009-2015

[6] Indeed, the approach is denominated Integrated Rating.

[7] As intended by [84]

Table 7.1: Quantitative SME rating. A few examples

#	Article	Data stream	Rating system
1	[101]	Chinese information provider, data from 206,149 enterprises	*Yes.* Logit model
2	[102]	Commercial Credit Scoring Data 2015 from the National Credit Bureau (NCB) of Thailand. The dataset contains 1 million SMEs with their credit history: loan amounts, default status, past due amount, past due days, etc.	*No.* Identification of principal component.
3	[70]	Chinese government's planned credit code, Alibaba's MyBank, AliFinance, Tencent's WeBank	*No.* The study gives a glimpse of the potential of big data for SMEs rating

7.4 Monitor the Trades

As recalled earlier, though most CRAs consider value chain variables in the rating process, the importance of these factors is diluted in the 10 percent weight of all non-financial factors considered. No certain data are available for banks, but it is likely the statistic might be similar.

Therefore, being the solvency risk being directly related to the cash availability of a firm,[8] the possibility to closely monitor the transaction flow, and thus to have an up-to-date assessment of the cash condition of a firm, together with the various degrees of interaction with the external SC environment, could potentially allow to overcome the scarce timeliness [101] and the lack of financial data [102] of the current approaches and enable a more reliable assessment of the impact on PD of operational performances.

The focus on the trades stems from the necessity to monitor the network parameters, as already clarified [12], and from interesting results from recent SCF studies, showing possible use for banking data to monitor default rates [101]. Specifically, the research (in table 7.2) showed the correlation of defaults with the following factors:

[8]No cash, no pay

Table 7.2: Determinants of SCF failures

#	Item	Description	Correlation
1	Taxable sales revenue	Level of profitability	*Negative*
2	Frequency of VAT payment	Stability of payment implies financial reliability	*Negative*
3	# of counterparties for VAT invoice issuance	Adaptability to SC relationships, resilience to default among partners	*Negative*
4	Frequency of VAT invoice issuance	Stability of cash inflows	*Negative*
5	Firm age	Ability to cope with stressed environment	*Negative*
6	VAT paid	The higher the VAT to be charged on customers, the less they will be loyal, the lower the cash inflows of the focal firm	*Positive*
7	Industry clockspeed	Drastic changes in demand structure, technology and industrial order will lead to the discontinuance of incompetent firms	*Positive*

Despite the study was tailored on the Chinese market, with a peculiar taxation policy, a similar approach could be or generalised to other settings.

7.5 Data Streams and Blockchain

As recalled multiple times, one of the biggest obstacles towards an effective firm credit rating is the data deficiency. Even the innovative approaches mentioned in the two previous sections cannot be implemented without the access to a detailed amount of information regarding the rated enterprises.

It turns out that a group of European banks [5], led by the Belgian bank KBC, are currently implementing a blockchain-based platform for the processing of SMEs transactions.[9] The aim of the application is to connect all parties of the transaction together: the buyer, seller, bank of buyer and bank of the seller and processing the process starting from order to payment and guaranteeing payment when all the agreement requirements were met. In this way, the application includes the functionality of Trade Finance services (letters of credit or guarantees especially used in international trade when customers do not trust each other or additional financing is needed).[10] Basically, it allows the parties involved in a transaction to monitor step by step the status of their deal, from the order to the invoice settlement. The application has been tested with

[9] Digital Trade Chain

[10] https://www.smebanking.club/portfolio/kbc-blockchain-based-app-sme-trade/

SME customers in different sectors and KBC Bank at the moment negotiates with said EU banks to roll out the service more widely.

A blockchain is an open and distributed database that can record transactions between two parties efficiently and in a verifiable and permanent way [59]. By design blockchains are inherently resistant to modifications in the data that once recorded, cannot be altered retroactively. The technology risen with the soar of Bitcoins, but its potentialities go way beyond the monitoring of e-currency transactions. Being privacy a huge concern for a system sharing sensible data, blockchains have evolved from the original permissionless form, to permissioned and private configuration. [11]

The platform is advertised as a safer and less time-consuming way for SME to secure their trade credit. Nevertheless, the potential of such a technology goes way beyond the trade credit management. If adequately leveraged, the data from the blockchain itself could be used as a proxy for a breakthrough improvement in the credit risk assessment for small businesses. Particularly, a widespread blockchain-based shared platform could potentially overcome the three main drawbacks of creditworthiness estimation for SMEs:

- *Backwardness and low responsiveness.* Through the shared record, banks could have access to up-to-date information regarding the monitored company.
- *Financial ratio.* The blockchain-based approach reduces – if not totally overcomes – the need to look at financial ratios to infer the creditworthiness of an entity.
- *Network interaction.* Blockchain information naturally reflect the interaction of a firm with the business environment. From the traditional two-party exchange of data, blockchain applications increasingly allow participants to reach multiple upstream and downstream SC partners in a peer-to-peer fashion [19]. Plus, blockchain data includes information regarding both the value chain parameters highlighted by [64], as well as transactional related data as pointed out by [102].

7.6 About Information Sharing

In the first chapter of this literature review, we mentioned that whenever SCF is not applicable, corporations must rely on a more traditional financing provider. In the abovementioned mathematical framework, i_{rated} (hereafter: i) is a parameter given by the model, that generically reflects the riskiness of a company. In the real world, and as we have previously defined, each credit exposure risk premium is composed by two elements: the first one, i_F representing default probability/creditworthiness of the borrowing entity, the second one i_P reflecting the characteristics of the specific project P about to finance. That is:

$$i = i_F(\text{PD}) + i_P(\text{PD,LGD,EAD,M})$$

Provided that the bank entity applies IRB approach to assess its regulatory capital, either FIRB or AIRB, but regardless from the method adopted by the bank to assess PD, we believe that a model that would be able to include SC-wide considerations – as the

[11] There are slight differences in term of the degree of integrity and consistency of the data among the three [52], but this goes beyond the purpose of this work.

one illustrated in the previous section – in the assessment of the PD, would significantly benefit both parties. We try to simplistically frame the go/no-go financing process of a financial institution [40]. It is reasonable to assume i ultimately depending from PD, as LGD, Exposure at Default (EAD) and Maturity of an exposure (M) are parameters depending from the size of the loan and by PD itself. Specifically:

$$\begin{cases} \mathrm{PD} > \mathrm{PD}_{\mathrm{max}} & \text{no financing} \\ \text{otherwise} & i(PD) \end{cases}$$

Where PD_{max} is a bank fixed threshold for which the counterparty risk is deemed too high to grant the borrowing. The implementation of SC data comes at a cost [84] [64] as it involves several stakeholders within the financial supply chain, but still, if this could allow a bank to ease the access to finance, there is the possibility for a win-win situation for both the parties. The reasoning is that the average PD estimation lowers there will be

- More granted borrowings for smaller player, as the estimation of PD more often will fall under the threshold
- Lower average interest rates,[12] to the benefit of the whole SC
- Reduced likelihood of avalanches bankruptcies, as consequence of multiple credit crunches. This, thanks to an increased resilience to disruptive events along the SC due to the improved credit availability. On this latter point, different studies [28]; [12]; [80] have argued the autocorrelation between default events and cost of capital.[13]

On the other side, the efforts for the financial institution will be justified by

- More accurate allocation of the credit [80], thus reduced the NPL rate and improved the profitability. The financial institution could in this way consolidate the role as a partner in the SC, capable not only to support clients' needs but also to advise and foresee them, thanks to the better availability and transparency of the information.
- Let PD^* be the default probability assessed to a generic actor i with the benefit of the supply chain information (opposing to the standard fashion, labelled as PD) and $G = G(PD)$ the total exposure of a financial institution in the given SC (while $G^* = G(PD^*)$ is the exposure with the supply chain information).

Let, eventually, $k(G, PD)$ be the likelihood of a avalanche bankruptcy event in the SC with the current exposure G and riskiness PD and let c be the cost, expressed as a percentage, that each actor in the SC has to bare for the disclosure of supply chain information. It is assumed, without loss of generality, that the costs c will be entirely sustained by the SC.

Then, the SC-based model is viable if the following condition holds:

- $G^* \geq G$. The amount of credit provided to each actor is at higher or equal than in the previous situation.

[12] For a loan of the same amount and with the same maturity

[13] Both in term of cost of borrowings and availability of capital

- $i^* + c_{\%} \geq i$. The costs for the disclosure of SC information do not overcome the reduction in interest rates, for any actor in the SC.

- $k(G^*, i^*, PD^*) \leq k(G, i, PD)$. The likelihood of an avalanche disruptive event will be reduced thanks to higher money supply. The default risk for the individual borrower will decrease as borrowing costs i will decrease and the net worth A will increase of an amount equal to $G^* - G - c > 0$ [12].

- $G^* \times i^* \times NPL^* \geq G \times i \times NPL$

If respected, the following conditions return a sustainable model.
Please note that:

- it is hard to quantitively estimate the likelihood or the impact of an avalanche bankruptcy, as they will be various and randomly widespread and that

- even if NPL^* does not have necessarily to be lower than NPL – provided that the increase in the invested capital G is higher – it is likely that small variation in i will yield a much higher oscillation of a bank's expected return, than whatever marginal change in G.

To exemplify this concept, let's assume the average interest rate in a SC reduces from 4 to 3 percent. It has been actually reduced by one fourth from its previous value. On the contrary, if the debt exposure in the same supply chain amounts, let's say, to € 500 million, an increase of € 50 million in exposures due to a more confident estimation of the PD represents only a 10 percent shift. It reasonable to assume percentage variation of the interest rate more significant than those in G, as, while the reduction in i affects more or less all the actor in the supply chain, the variation in G concerns those smaller corporations who used to experience a more difficult access to the credit. This is to say that, even under a mathematical point of view the NPL^* does not necessarily have to improve, under a more realistic perspective it is likely that it must anyhow improve to counterbalance the uneven variation of i and G.

Furthermore, said model must be able to overcome agency problem related to the information sharing, meaning that, the equilibrium generated by the new model must be pareto-optimal. This means that, on the bank side, the outcomes (G, i) of this multi-actor-like game must be optimal, given the amount of information provided c, while, on the other side, there must be no incentives for opportunistic behaviours in the process of information sharing (e.g. collusive behaviour of the rated entities). Specifically:

- *Moral hazard.* The bank could not be able to exploit the added information at their exclusive advantage. (Sub-optimal reduction of G and i)

- *Adverse selection.* Companies cannot have the possibility to hide or mock any information, for instance through collusive behaviour, to their own advantage and in a way that the lender no longer can discriminate the lemon borrowers nor adequately reward peaches ones.

Part III

Objectives

Chapter 8

Research Questions

8.1 Wrapping Up

In chapter 1 we analysed the extent of SMEs funding gap in Europe. Access to finance is still an issue for to smaller business, and the NPL ratio is substantially higher than in other regions of the developed world.

Supply Chain Finance, as seen in chapter 3, attempts to solve the problem by leveraging on information asymmetries between supply chain partners and banks, with the objective to lower the cost and increase the availability of capital or, alternatively, with the aim to decrease NOWC by offering trade credit or advanced methods of payment and inventory management. The benefit of SCF solutions are very often limited to the first tier in the supply chain, i.e. to those companies that directly trade with the focal company.

In theory, the literature financial risk assessment is extremely wide. Likewise, the panorama of mathematical frameworks in its support, as we briefly go through in 6, is extensive. In fact the methodologies for assessing the creditworthiness of a borrower, even if of crucial relevance, are still vastly underdeveloped. A multitude of different approaches have been developed to account for the most disparate determinants of the creditworthiness of a corporation. However, due to various reasons, as shown in chapter 5, SMEs-specific approaches have been investigated less from scholars with respect to those for larger corporation. On one hand, CRAs have very few incentives to develop tailored model for smaller enterprises, nor SMEs could easily justify the budget for it. On the other hand, banks, for their convenience, very often apply top-down methodologies. Portfolio-invariance assumption - from Basel framework, as seen in chapter 4 - does not help in explaining idiosyncrasies at obligor level and there is no evidence that the supporting factor brought any significant improvement to the financing problem. Scoring methodologies are predominantly based on financial ratios. while overlooking the importance of the interaction of SME with the surrounding business environment.

One of the major drawbacks of the innovative literature on credit risk, as seen in chapter 7 is to be mostly theoretical. Many high-level approaches are being proposed, few of them have been eventually implemented, verified and corroborated. This, due to the fact that these new models often pivot on non-financial variables, and they consequently tend to suffer the lack of data availability. This is mostly due to the reluctance of the involved parties to disclose their sensible information. This is the stake to pay for going beyond the dichotomy financial performances – credit risk. This is is the main reason for which financial ratios account up to the 90 percent of a credit opinion [92] but also a significant dilemma, since these approaches could potentially yield better results if applied [72] and it but the cost for their development and deployment could be overkilling.

For these approaches the assessment of the validity of the model itself its particularly critical. To certain extent, a numerical simulation of the behaviour of one of these models might generate some interesting preliminary results that might foster further research.

To these regards, the blockchain technology might be the lever through which those theoretical approaches would eventually see the light. The fact that major European banks are now partnering towards an extensive deployment of this technology for the SMEs market, it is a huge opportunity to push research efforts in the same directions.

8.2 Gaps and Issues of Traditional Credit Rating Models

Improved awareness on credit risk of smaller obligors might significantly ease the access to capital for smaller businesses. Going beyond the dichotomy financial performances - credit risk, could be a way. Specifically, supply chain may elicit precious information, otherwise hidden, on the actual creditworthiness of an enterprises.

We summarize the main lack of the traditional credit rating models, as they have emerged form from the literature review, in two core problems:

1. *Backwardness.* The assessment of the probability of default is done on mostly a yearly basis. Models are fed with static information and information from the financial statement are already outdated when the financial statements are published.[1]

2. *Decontextualization.* The importance of the supply chain context is often neglected. Whenever considered, supply chain information has anyway a low relevance. On the contrary, financial ratios and wrong distributional assumptions neglect the idiosyncrasies of multifaceted realities like SMEs are.

8.3 Research Questions

On these premises, two main questions arise:

Q1. How do the supply chain performances influences the solvency risk of an enterprise? Again, this is particularly relevant for SMEs, as their performance are strongly dependent from their surrounding context [12]. In absence of real world experience and feedbacks, and in given the scepticism of some practitioners, how is it possible to prove the good performance of the novel approach? Any insight regarding the performance of this model might stimulate further development of the literature in this direction as well as the interest of practitioners.

Q2. How to frame a reactive system for credit rating? This is a crucial quest

[1] Usually, three months after the end of the financial year.

for SMEs and for their banks, as SMEs performances are, in general, exposed to high volatility and uncertainty. What would be a viable framework to leverage the potentialities of the blockchain technology under the credit rating perspective, capable to deal with the agency problem arising from the sharing of sensible information.

Chapter 9

Methodology

We will tackle the objective of developing an alternative credit risk assessment framework from two sides. Both approaches will aim to capture hidden supply chain information to elicit the creditworthiness of the rated company.

We refer to the first approach as transaction based. Ideally, we would be able to analyse the relationship and the distress in the chain by monitoring the credit chain reliability [1], [5]. Theoretical foundation to the approach can be found in the work of [12]. Transaction records are online data, meaning that they are collected as they are generated and they can be constantly monitored. Such data could be leveraged to provide up-to-date creditworthiness appraisals, thus solving the backwardness issue of current credit risk models.

The second, and last, method relies instead on NOWC proxies. In absence of large data streams from the supply chain, whose availability is definitely restrained, data latency remains an issue. To counter that, working capital measures could be good predictors of the state of a company, in that they are proxy the cash-to-cash cycle [44] and they could potentially extract information about credit worthiness of supply chain actors [88], to potentially increase the forecasting capability of the model.

9.1 Transaction Based Model

The methodology for this model develops in two parts. In the first one, a conceptual framework to address the highlighted issue will be developed and analysed under an econometrical point of view, looking at the incentive for to collaborate and expected benefits form the parties. The framework will be based on the current research [64] of the observatory for Supply Chain Finance of Politecnico di Milano and other scholars [101].

The second part will consist in the development of a fictitious business environment. Through numerical simulation of a 5-tier supply chain environment along a multi-period scenario, the objective is to prove the promptness and the statistically-significant forecast capability of a set of supply chain-related CRFs. The idea is to repeatedly monitor the rated firm in the chain, to asses how and to which extent SC performances [64] can be effective assumed as predictors of credit risk. The significance and the discriminatory power[1] of the CRFs will be tested through logistic regression, which is our method of choice. Indeed, among those shown in chapter 6, this is perhaps the most widespread

[1]The ability to correctly classifiy defaultin and non defaulting companies

approach for classification. Assumption throughout the modelling process have been aimed to mirror some salient characteristic of the business environment of a small mid-sized enterprise. The choice of the numerical simulation is dictated by the need to overcome the difficulties in obtainig data on real companies, by framing a realistic scenario where to observe and analyse the effects of supply chain interactions on credit situation. Eventually, the aim of the study is to set a path for incentivize actors in disclosing sensible data for more thoughtful analysis. For similar reasons, an analogous approach has already been employed in the SCF academic world [54].

A training sample of scenarios is generated through simulation. The rated companies are monitored and classified in two categories: peaches, alias the creditworthy borrowers, and lemons, the bad ones. The discriminating threshold between good and bad performances is determined by the number of days past due. On this premises, the simulation run until either it reaches its end or the company is 90 days past due [9].

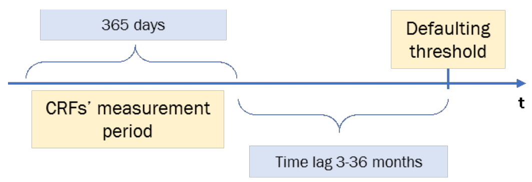


Figure 9.1: Lag from default

Trailing 365-day CRFs, at different lags, are calculated and stored. After generating the training sample, a bivariate logistic regression model is built and tested with a new set of simulated companies. Companies in training and testing sample have been randomly sorted from the generated dataset. Specifically, 80 percent of the data serves to the purpose of model training, and the remaining 20 percent is used for testing. The analysis tests the predictive capability of the CRFs at multiple lags from the final state of the sampled companies (3, 6, 9, 12, 18, 24, 30 and 36 months). Data analysis is performed in the `R` environment.

9.2 NOWC Based Model

We retrieved historical data series from a private database of European companies. To be aligned with the scope of the work, we collected a sample of defaulted and active companies, that are classifiable as SMEs, according to the EU definition. We further narrowed down the scope of the research excluding financial and insurance companies, outside our interests, as detailed in table 9.1. More details on the company sample in figure 9.2 and 9.3.

Note that,

$$NOWC \sim f(\text{Accounts Payables, Accounts Receivables, Inventories})$$

Therefore, for each company, we retrieved 4-year[2] historical series for the following CRFs:

- Inventory turnover
- Payables days

[2] Last-available + 3 previous yoy datapoints

- Receivables days

Considering time series longer than 4-year brought little-to-nothing improvement to model accuracy.

Table 9.1: Database queries

Search filter	**Values**
Company status	• *Active sample* 1. Active • *Defaulting sample* 1. Active: (rescue plan, default of payment, insolvency proceedings) 2. Inactive: (in liquidation, bankruptcy, dissolved)
No. employees	< 250
Operating Revenues	< € 50m
Total Assets	< € 43m
Sector(s)	Agriculture, forestry and fishing, Mining and quarrying, Manufacturing, Electricity, gas, steam and air conditioning supply, Water supply, sewerage, waste management and remediation activities, Wholesale and retail trade; repair of motor vehicles and motorcycles, Transportation and storage, Real estate activities

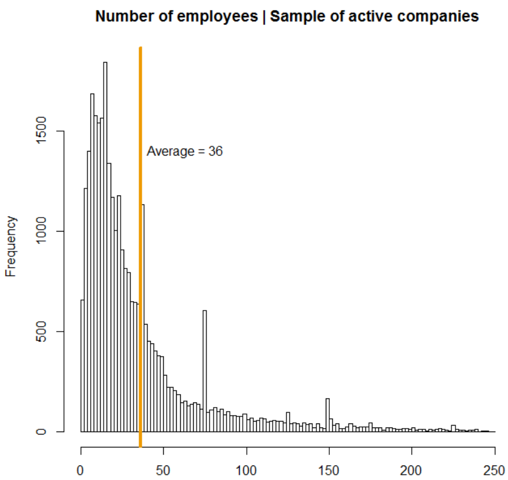


Figure 9.2: Internal risk *(No. employees)*

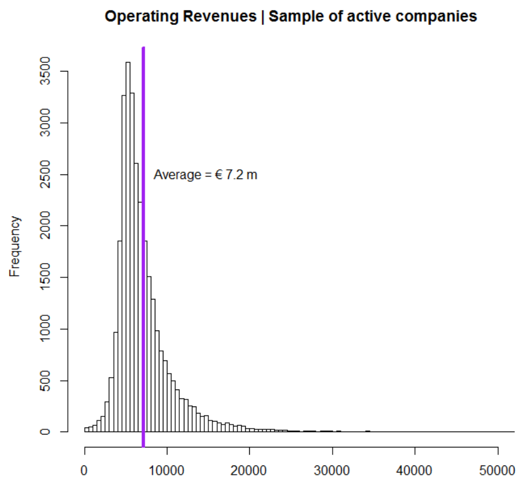


Figure 9.3: Network risk *(Op. revenues)*

We purposely selected non-financial proxies of Accounts Payables (AP), Accounts Receivables (AR) and Inventories (I), to avoid the sphere of financial performances, in the attempt to extract information about supply chain relationships [88] and on operational performances.

In a first phase, we retrieved a set of 140,000 entities and, after cleaning the data by excluding companies for which the historical series were not entirely available, we were left with a sample of 50,350 companies, of which, 30,511 active and 19,839 defaulted. It is not a surprise that the sample is unbalanced towards the active companies (61% – 39%). This will be taken into account, but do not preclude the feasibility of the analysis. We classify the companies via a non parametric model, from the class of multilayer perceptrons, alias neural network. This kind of models, as seen in chapter 6, can explicit information from complex relationship of the input data and work particularly well if, as in our case, the training sample is large. A second analysis is performed on a lager sample of 212,747 companies (after data cleaning), of which, 178,729 active and 34,018 defaulted. Without surprises, this sample is even less balanced than the previous (84% – 16%) due to the fact that defaults are a fairly a uncommon event and, as the size of the sample approaches the population size, the proportions of the categories are likely to better approximate the real one, which is normally lower than 10% [36].

Part IV

Transaction Based Model

Chapter 10

Credit Risk Factors

Against the pitfalls highlighted in chapter 9, this section develops a framework to tackle backwardness and decontextualization of previous models. The objective of this transaction based framework is to target simultaneously internal and external sources of risk related to the supply chain and translate them in term of probability of default, in the terms already provided. For these purposes, two types of risk variables are incorporated in the framework: operational and transactional, which will be addressed afterwards as Credit Risk Factors (CRFs).

10.1 Operational Credit Risk Factors

The selection criteria proposed to evaluate operational CRFs comes from vendor rating literature. Among the numerous KPIs proposed by scholars [91], three eminent operational variables have been already considered by the Observatory for Supply Chain Finance of Politecnico di Milano in its study on creditworthiness [80]: quality, punctuality and conformity of production . The rationale is that a worsening of such performances might indicate repeated internal failures, bad order management and more in general, any sort of condition that might reduce the production output,[1] following a general reduction of efficiency and thus leading to a decrease in the P&L top line and therefore (probable) financial difficulties, in terms of capability to repay debtholders.[2]

Among those, the transaction based model includes timeliness (alias punctuality) as internal CRFs of the framework. Timeliness it is strongly tangled with the cash-to-cash cycle: a measure bridging inbound material activities with suppliers, manufacturing operations, and outbound sales activities with customers [44]. This CRF can be monitored by comparing the effective delivery date against the due one.

Table 10.1: Operational performances

Name	Metric	Literature
Timeliness	Consignment Date – Due Date	[80]

In the framework of the simulation, the production lead time of a batch is set to be $\simeq 1$ period. In fact, as it will be explained later, all the orders have different size but

[1] In terms of both quantity and quality.
[2] Mainly consisting of banks.

they are normally distributed so that it is reasonable to expect such production lead time, under non distressed conditions. This is a reasonable approximation if order sizes are nicely distributed, which is not unreasonable. In a real world setting, should this assumption not hold, the model would require, for each order, the punctual due date for each order.

10.2 Transactional Credit Risk Factors

Transactional variables involve loan/payables settlement performances as internal CRF as well, as suggested by previous academic works such as [102], [101]. Specifically, the framework will consider the frequency of Value Added Tax (VAT) transactions. The scope of this variable is to proxy the liquidity of a SME, overcoming the lack financial data from reports, if any, and the backwardness of financial statement's information. This result is achieved by tracking the frequency of cash inflows/outflows (corresponding to individual VAT transactions) and to infer early signals of potential financial liabilities. Specifically, this variable is set to monitor the reliability of the downstream company in honouring its financial liabilities. That is to say, VAT purchases, i.e. those for which a payment occur, should equal the number of orders processed by the upstream tier (corresponding to VAT sales of the upstream entity). If the two does not match, the buyer did not honour its obligations, causing the supplier to invest financial resources and to immobilize production capacity without any returns [12], or that ,to a lesser extent, the supplier cannot keep the pace with the demand from downstream

Table 10.2: Transactional performances

Name	Metric	Literature
Frequency of VAT transactions	VAT Purchases – VAT Sales	[101]

It shall be noticed that Net VAT transactions could strongly depend on the industry sector and on the lotting policy. This is not an issue per se, but should be taken into account when generalizing the approach. It is not uncommon that credit risk model are tailored country or industrywise, so should ours. In the simulation framework, as proposed by [12], we assume this variable to be distributed with first moment $\simeq 0$.

10.3 Internal Risk

Internal risk is the likelihood of negative downturn within a company itself. The incorporation of internal risk management perspective in the proposed framework does not serve to foresee the impact of disruptive event like natural catastrophes or similar, but rather it aims to closely monitor early signals of performance decay that might ingenerate a first-type bankruptcy, in the sense previously defined [12]. The research proposition that we raise is that a close monitoring of the internal CRFs (transactional and operational) could lead to an improved foreseeability of the current condition and give sensible indications concerning the eventuality of an incoming credit default. The rationale behind this proposition is that a worsening of such performances might indicate repeated internal failures, bad order management or more in general, any sort of condition that might reduce the production output. Reduction in efficiency naturally leads to a decrease in the P&L top lines and therefore (very likely) financial difficulties, in terms of capability to repay creditors.

We assume that each company in the supply chain has access to a bank overdraft, i.e., whenever its cash situation makes impossible an immediate settlement by own funds, the transaction payable is settled on the delivery date by a financial intermediary, who in turn will collect its credit after a certain period from the buyer entity, with some interests. This allows the company to temporarily pursue its business even when it does not posses the financial resources enough. In this situation, the a company benefit from fictitiously larger days of payable outstanding, though at an increased cost, while its suppliers can cash their receivables on time, and the bank invest the largest amount of capital in the system, leading to higher returns. This simplification will reduce the complexity of the simulation as the bank may in theory decide not to allow any overdraft. However, as the work is on creditworthiness, it seems reasonable to stick with this simplification, being the final goal that of determine, how long can a financial intermediary entitle a borrower of a credit line. As a bank overdraft is likely to be denied if the customer is bad debtor, it is reasonable to allow it as long as the company does not show excessive signs of liability.

10.4 Network Risk

We define network risk as the likelihood of a negative downturn within a company value chain, that could in turn ingenerate a second-type bankruptcy within a company, as previously assessed [12]. The CRFs related to network risk that this framework considers are the same as those describing internal risk. The only difference is that they are in this setting used monitor to companies along the supply chain of the rated company. Given that the default risk of each supply chain partner is more or less directly related to the own risk of the company, the framework shall weight external risk factor within the own risk of the company, according to the degree dependence of the focal company by each given supplier/buyer. The extent of these dependences is defined, in case of buyers, as the impact on

1. overall revenues, in case of buyers or
2. cost of goods sold in case of suppliers.

This set of risk factors will be hereafter referred as external CRFs. Anyway, in its current state, the simulation assumes only one partner upstream and one downstream.

10.5 The Transaction Unity

The core of this model is the transaction unity: an elementary element that consists of all the instances related to the production process of an order, from the order issuance date, through the production process up to the delivery of the product(s) from the supplier and the settlement of the payable by the buying company.

The proposition is that by looking at each individual transaction of the rated company would be possible to track the CRFs and therefore assess its credit risk profile.

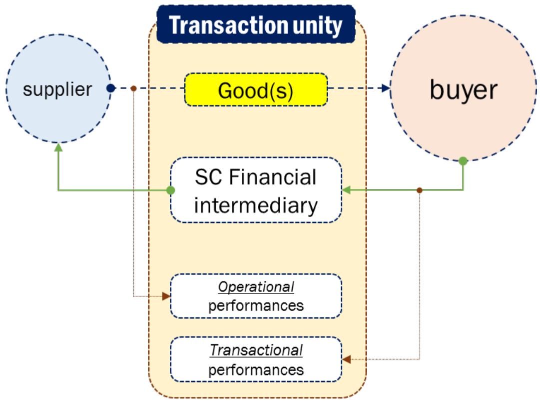


Figure 10.1: Transaction Unity

Each transaction will contribute to the definition of the credit risk profile of the rated entity. Transactional data could potentially overcome the backwardness of traditional model, as they are constantly up-to-date . Therefore, the proposed model is targeted to financial intermediaries, as banks are, or to whomever should have the ownership on these data [29]. In its theoretical formulation, the approach aims in assessing credit risk by looking at the supply chain in its entirety . However, it is unlikely that a unique financial entity could cover the broad spectrum of an entire supply chain. To these regards, initiatives like the Digital Trade Chain (DTC) promise to be an excellent support to the solution, in order to have a constantly up-to-date shared ledger where to gather and retrieve all the transaction data needed by the model. Specifically, the DTC itself should start rolling out late in 2017, partnered by a group of seven major European bank, with the objective to deploy a blockchain-based platform for the processing of SME transactions. The analysis of the ensemble of transaction units will allow to provide further information regarding the condition of the company.

10.6 Upwards/Downwards CRF

A final element worth noticing in the framework is something hereafter referred as the directionality of CRFs. The two categories of CRFs that we have included in the framework allow to assess either the risk of the entity upstream or, conversely, downstream the transaction unit.

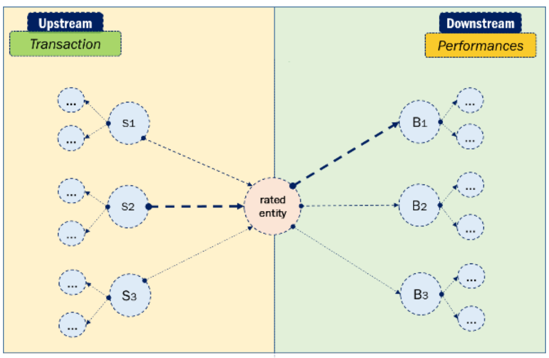


Figure 10.2: Internal risk *(inward looking)*

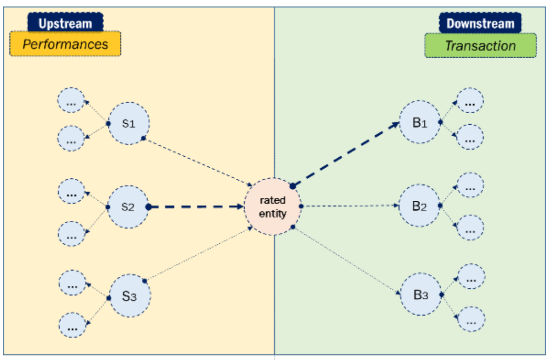


Figure 10.3: Network risk *(outward looking)*

Specifically, operational CRFs are upwards looking, as they allow the assessment of the performances of the supplier involved in a transaction. On the contrary, transactional CRFs are downwards looking and monitor the performance of the buyer entity involved in a given transaction. This implies that the internal risk of a rated company can be fully measured only looking at both upstream and downstream transaction units. Comparably, this gives hints for the analysis of the external risk as well, where to assess upstream risk, will be employed operational CRFs and transactional CRFs for the downstream part. This is better explained by the illustrative diagrams in figure 10.2 and 10.3.

Overall, the table 10.3 might further help in clarifying the cross combination of CRFs.

Table 10.3: CRFs summary

	Upstream	*Downstream*
Internal	Transactional CRF	Operational CRF
Network	Operational CRF	Transactional CRF

Chapter 11

Hypotheses

According to the abovementioned framework, here the hypotheses that are going to be tested in the following chapter.

Table 11.1: Hypotheses

Hypotheses	**Expected correlation with business failures**
Internal CRF	
H1: Bad timeliness performances of the rated company, intended as abnormal production lead time are indicator of financial liability	*Positive.* An increase in production lead time entails operational distress and, therefore, a decrease in P&L. [80]
H2: Reduced VAT frequency of the rated company, as it is defined, is indicator of financial liability	*Positive.* A decrease in VAT frequency is symptom of business failure in the supply chain [101]
External CRF	
H3: Bad timeliness performances of the upstream company, intended as abnormal production lead time is indicator of financial liability in the rated entity.	*Positive.* Distress in the supply chain can deteriorate credit situation in the adjacent tiers [12].
H4: Reduced VAT frequency of the downstream company, as it is defined, is indicator of financial liability in the rated entity	
Overall Framework	
H5: Supply chain performance, as they have been defined, are good predictors of supply chain failure	

Hypotheses are related to *RQ1* in that they aim in assessing the forecasting capability of supply chain based indicators and to *RQ2* as the CRF monitoring architecture is supposed to rely on online data.

Chapter 12

Side Considerations

12.1 Importance of the Interrelation Among Operational and Transactional Variables

It is of crucial importance to recall the strict interrelation of the two types of CRFs, operational and transactional: monitoring just at one of the two indicators could lead, in the short run, to false positive and thus, to a biased assessment of the creditworthiness of a company, as highlighted in the table 12.1.

Table 12.1: Biases

	Operational	**Transactional**
False positive	Order stagnation	Liquidity buffer
False negative	Demand excess	

12.1.1 Order Stagnation

Company's operational performances may seem positive despite the company barely produces anything. This issue cannot be highlighted if not by looking at the transactional performances, that will start worsening as soon as the company revenues are no longer able to cover fixed costs. In terms of the selected CRFs, this would mean:

- unchanged Timeliness performances (internal CRF), but
- deteriorating Net VAT transaction CRFs downstream (external CRF).

12.1.2 Liquidity Buffer

One company payments track could look unchanged in a short/medium period while operational performances worsen. This happens if the company has either an abundance in cash, due to previous better performances, other businesses line or, in the worst case, if it manages to borrow money to settle previous debt. The risk of this situation cannot be detected without looking directly at the operational performances. In terms of the selected CRFs, we would expect

- a decay in Timeliness performances perceived from downstream (internal CRF), whilst
- Net VAT transaction stable (internal CRF), as the company manages to pay its suppliers with its liquidity buffer.

12.1.3 Demand Excess

A sudden increase of demand might lead to a temporary decay in the operational performances. For instance, the production might not be able to promptly fulfil the increase in production or the quality/conformity of the output temporarily decreases due to the accelerated production regime. Transactional performance should anyhow reflect the improved situation of the demand. This should imply

- a worsening in Timeliness performances (internal CRF), but
- an improving Net VAT transaction (internal CRF), as the company buys part more supplies to face the positive demand shock.

Analogously, a sudden soar in the demand could temporarily induce a shortage of cash, so that a company might experience some difficulties in meeting payment due date for previous order. If operational performances are alright, there should not be reason to worry, as the situation would quickly even off as the work in progress is sold. This signifies

- stable Timeliness performances, but
- reduced Net VAT transaction (internal CRF), as the rated company temporarily doesn't manage pay its all the increased supply in time, because of too long cash-to-cash cycle. If the company perform well, this temporary unbalance should quickly resolve.

12.2 Discriminate Double False Positive / False Negative

Sometimes looking at internal CRFs might not be enough to assess the situation of a company (see table 12.2).

The number and the size of the transaction unities can help to discriminate a situation of either double false positive or double false negative, coherently with [101].

Table 12.2: Double biases

	Operational		**Transactional**
False positive	Order stagnation	+	Liquidity buffer
False negative	Demand excess		

Specifically, a situation of simultaneous order stagnation and liquidity abundance (and therefore no immediate alarm signal from operational/transactional performances) could be detected through a decrease of either or both the overall number and average size of the transaction unities processed in the most recent periods. Likewise, worsening performances due to excessive demand could be detected in the same way (increased absolute number of transaction unities). We deem this eventuality should be quite seldom.

12.3 Negative Biases

It is important to remember that the objective of the framework should not merely be to highlight critical situations, but rather to allow banks to better discriminate among good and bad performers, with the double objective to reduce the need for regulatory capital and the NPL ratio one hand, and to ease the cost of capital to companies whose performances are improving on the other.

This directly reflects on the discriminating threshold of the predictive model. In-detail comments regarding specificity and sensitivity will be made further on (see chapters 16 and 21), but, as a general idea, the model must find a balance between the ability of the classification model to be reactive in detecting defaulting companies (i.e. sensitivity) and at the same time it must take care of the fact that no company should be mistakenly classified as not worthy of credit (i.e. specificity). It is in the interest of financial providers that the model is as sensible as possible, in order to avoid the issue of NPLs, but, at the same time, the access to credit of SMEs can be improved if the model does not tend to classify creditworthy companies as bad borrowers.

It is indeed possible to tune these two parameters in a way so that the true positive rate (sensitivity) equals the true negative rate (specificity), and so that the so-called α[1] and β[2] errors are minimized.

12.4 Overfitting

It is important for the model to be parsimonious. This means that multiple predictors should not explain the same effect. To these regards, pairwise correlation between candidate CRFs is tested. Redundant variables should, when needed, be excluded from the model.

12.5 Opportunistic Behaviours

In theory, as the framework of the credit rating model envisages the support of a blockchain platform to act as shared ledger for information, there should not be inconsistencies for the most part of the data. Though extremely unlikely, due to the robustness of a shared ledger, some inefficiencies could potentially arise.

12.5.1 SMEs Side

It could be argued that two firm involved in a transaction may provide fictitious data regarding the transaction itself, notably in term of quality and conformity of the delivery. The parties might, in theory, enter some outside agreement that would benefit the two. Specifically, the upstream company would see its operational performance to inflate,

[1]The probability that a creditworthy company is misclassified

[2]The probability that a defaulting company is not detected

reducing the premium to pay on the internal CRF, whereas the downstream party would see its external operations CRF reduced, as the performance of the supplier are fictitiously improved. The model itself cannot prevent the issue, even but the collusion is naturally hindered by two main factors:

- In the long term it is not convenient for a company, whether up or downstream, to do business with bad-performing partners.
- Operational performances are assessed according to the overall business of a focal company. This means that the collusion, to be effective, should involve al the partner of a given entity, and the increased number of required parties makes collusion harder to achieve.

12.5.2 Banks Side

On the other side, banks could potentially decide to retain all the benefit arising from the improved credit risk assessment, in avoiding to provide a favourable discount rate to the enterprises or, conversely, excessively penalising those in difficulties. There is not much that a SME could do to tamper this issue.

To this regard, we argue that the competition for the loan market arising from the number of partners in the blockchain-based shared ledger, should be enough to prevent moral hazards from the bank side. An opportunistic behaviour of banks could lead to a tit-for-tat response of the borrowers, inclining reciprocal trust and making the implementation and the maintenance of the system more harder. The market for loans should be enough mature to stimulate active collaboration among the parties, as envisaged by [80], where the role of the bank is of primary importance for the surviving of the supply chain.

Chapter 13

Description of the Simulation

The simulation engine model has been developed in Excel and Visual Basic for Applications (VBA). The reason for the choice of these tool was predominantly the convenience of Excel in handling complex and strongly tangled tables of data and the intuitive and embedded VBA language to model such relationships. The time horizon for the simulation data is approximately 2500 periods(either $\simeq 6.8$ 365-day-long years or 10 250-working-day-long years). This threshold does not represent any conceptual assumption on the behaviour of the supply chain, but rather, has been dictated by the trade-off between the ability to observe the effect of changes in the relative performances of the actors involved and the computational requirements to run the program. No loss of generality is though implied in the choice. As a reference, [12], run their supply chain simulation over "few thousand periods", which is coherent with our assumption.

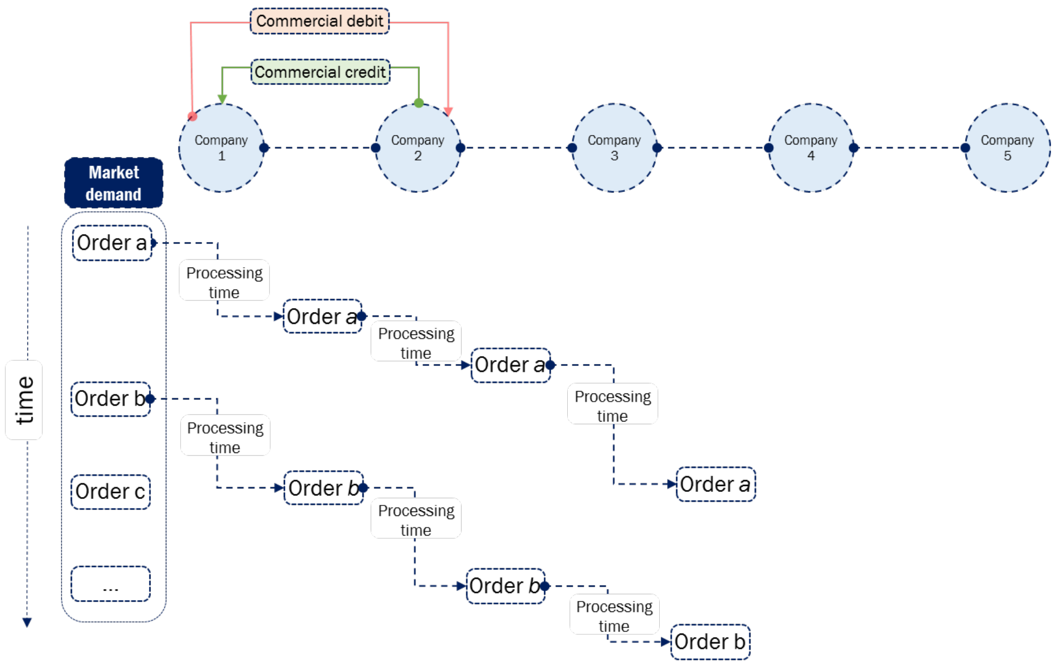


Figure 13.1: Schematic representation of the simulation

The program simulates the effect of the interaction of five companies on five different levels. As we are interested only the effect of the relative performances among the players, we consider this limitation not to constitute a loss of generality of the problem. Indeed, from the point of view of the rated company, the interaction with one big entity, could be easily seen as a combination of the interactions with multiple and smaller entities (at least in a first approximation). Each company has access to bank overdraft. Commercial credit is in place.

13.1 Economic Environment

The demand is modelled according to a Poisson process (blue bars in figure 13.2) with λ equal to the forecast annual demand (orange line in figure 13.2), which in turn is defined in terms of number of orders per years. The parameter λ itself evolves in time as a markov Chain-like process,[1] to reflect changes in the expected demand. At each period (equivalent to 1 day), a certain number of Poisson events is generated according to the parameter λ. Not being interested in the effect of significant variation in the market demand, the markovian process of λ is bounded so that cannot assume extreme positive (negative) values. The choice of the Poisson distribution of orders has been dictated by the need to simulate a discrete process. A continuous approximation would not have truly reflected the SME environment, where changes in the number of orders are not negligible with respect to the amount of orders in the previous periods. To each order generated, it

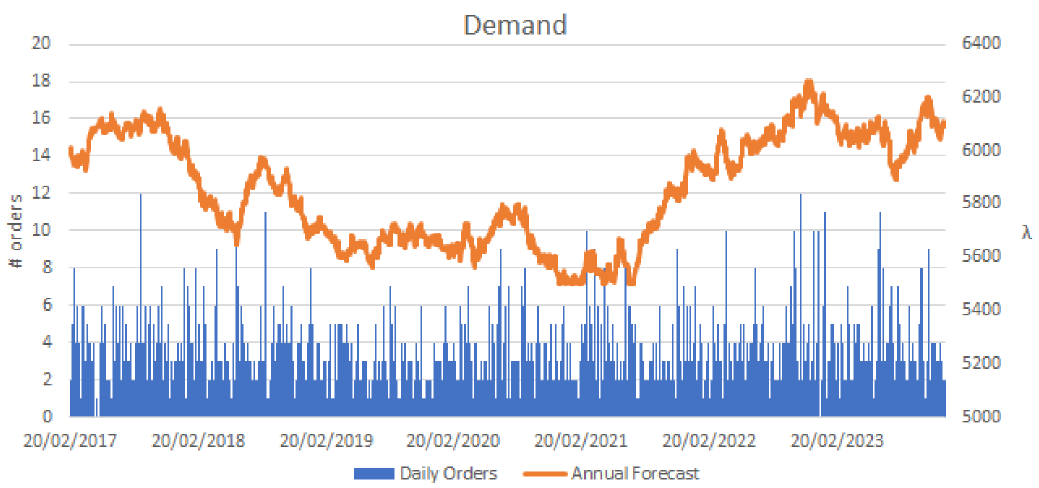


Figure 13.2: Forecast vs. actual orders

is associated an order size. The distribution of order sizes is assumed to be normal. The processing of each order begins upstream and it is carried out along the SC. The model assumes a linear technology, for which each input corresponds to an equal output [12]. A unique production factor is assumed as well: L, representing the production rate of each company $L = \left[\frac{\text{Units}}{\text{Period}}\right]$. At each stage, the input is processed according to the current rate of production, which changes in time. At initiation, each company is endowed with a set production rate L_0, sufficient to cover the average daily demand dictated by the current demand forecast λ_t. The simulation assumes L_0 to be the maximum production rate of a company. There is no possibility to increase the parameter, through investing money. Despite being a reasonable assumption in the short term, this cannot be said for the

[1] Alias random walk. Specifically: $\lambda_t \sim \mathcal{N}(\lambda_{t-1}, \sigma_0)$

medium long term. As the model develops at the boundaries of short and mid run, and since the demand is bounded, we will take this assumption as reasonable.[2] Changes in the production capacity, can only decrease the production capacity below this maximum threshold and are described by a Markow process, where L+1 only depends from the previous value L_t and it is normally distributed with $\mu = \mathrm{L}_t$[3] and standard deviation σ, set at initiation. Orders are processed according to a first-in-first-out logic. Stocks of raw materials[4] and work in progress[5] are stack in the queue. Finally, each company has a maximum number of items that can hold in the queue. This implies that one company will purchase up to the point where it has place in its queue. This is coherent with the assumption of limited warehousing space in a firm, especially true for smaller businesses and it is also reflect the reasonable assumption for which that a company will stop purchasing from suppliers if it cannot keep the pace with the demand. Since the demand is bounded, and no other factors are involved, increments in the stock size can only be accounted to a decay of the production capacity. The production is just-in-time; hence, under non distressed condition, no stock should be held by the upstream entity, nor the production can be resold to another player than the one for which it has been produced. Loss due to missed purchases entirely account on the p&l of the upstream entity.

13.2 Financial Environment

Revenues are directly proportional to the quantity of output sold [Orders Processed × Price]. At each level of the supply chain, the price is determined with a mark-up principle and it is assumed to be the market price. Hence the company cannot trigger this lever to improve their results.

Costs encompass different elements. First and foremost, the Cost Of Goods Sold (COGS), i.e. the price paid to the upstream side. Secondly, stock warehousing cost are considered. Expressed as a multiple of a given unitary warehousing cost, they aim in reflecting the spoilage of the stock, the opportunity cost of missed productions and the cost of the warehousing itself. As normal fluctuation in the demand could naturally ingenerate a queue, this cost item kicks in only when a set threshold of stock is exceeded. Eventually, fixed costs are considered proportional to the production rate, coherently with the assumption that, this cost item is directly proportional to the size of the production. Overall:

$$\pi_t = \pi_{t-1} + \mathrm{R}_t - (\mathrm{COGS}_t + \mathrm{C}_t)$$

where, at each period t, π is the profit, R represents revenues, COGS is the cost of the purchase of raw material and C the sum of the two latter cost items as defined. We said that commercial credit is in place, therefore, the level of cash k_t at each period is defined as:

$$k_t = k_{t-1} + \mathrm{R}_{t-r} - (\mathrm{COGS}_{t-p} + C_t)$$

[2] Moreover, keep in mind that changes in the maximum production rate are likely the effect of strategic decisions which are not easily modelled.

[3] The production capacity at period t

[4] i.e. not-yet-processed inputs.

[5] i.e. partially-processed inputs.

where, at each period t, k is the level of cash and the other items are as stated just above. Note that R and COGS refers to a past number of days, defined by r (days of receivable outstanding) and p (days of payable outstanding). r and p are determined at origination and has to be assumed as the average value of debit (credit) outstanding allowed by suppliers (to buyers).

In table 13.1, a detailed explanation of variables and parameters of the simulation. Part of the notation has been previously omitted for simplicity.

Table 13.1: Simulation parameters

		Formula	**Metric**
Level in the SC	i		
Time Period	t		[Time]
Production Rate	$a_{t,i}$		[Units/t]
Warehousing Capacity	W		[Units]
Queue	$Q_{t,i}$	$\max(Q_{t-1,i} + I_{t,i} - O_{t-1,i}; W)$	[Units]
Input Quantity	$I_{t,i}$	$\begin{cases} W - Q_{t-1,1} - O_{t-1,i-1} & \text{if } Q_{t,i} = W \\ O_{t-1,i-1} & \text{if } Q_{t,i} < W \end{cases}$ [6]	[Units]
Output Quantity	$a_{t,i}$	$\begin{cases} a_{t,i} & \text{if } Q_{t,i} \geq a_{t,i} \\ Q_{t,i} & \text{if } Q_{t,i} < a_{t,i} \end{cases}$	[Units]
Price	$p_{t,i}$	$p_{t,i-1} \times (1 + \text{Markup})$	[Money]
Revenues	$R_{t,i}$	$p_{t,i} \times O_{t,i}$	[Money]
Cost	$C_{t,i}$	$C_{gs;t,i} C_{w;t,i} C_{gs;t,i}$	[Money]
Cash Inflows	$K^+_{t,i}$	$p_{t-r,i} \times O_{t-r,i}$	[Money]
Cash Outflows	$K^-_{t,i}$	$p_{t-p,i-1} \times I_{t-p,i}$	[Money]
COGS	$C_{gs;t,i}$	$p_{t,i-1} \times I_{t,i}$	[Money]
Warehousing Cost	$C_{w;t,i}$	$\max((Q_{t,i} - \text{Order Size}) \times \%; 0)$	[Money]
Fixed Cost	$C_{gs;t,i}$	$a_{t,i} \times \%$	[Money]

At initiation, all the financial parameters[7] are set so that – ceteris paribus – the profit would remain stationary in time.

Being the work focused on credit worthiness proxies, the aim is to be able to foresee the cash situation of a company in order to be able to correclty assess its likelihood to go default. To these regards, tracking the cash is of crucial importance, as financial liabilities can only be repaid in cash.[8] Once the cash situation is negative, a company does not automatically default, rather, it will start paying back its debt beyond the due date.[9] According to BIS definition [7], a credit default happens if an exposure beyond 90 days past-due . In practice, and I would say, especially for commercial credit, there might me some flexibility, and the default can be subjected to the overall amount of debt which is, in fact, past due. Nevertheless, to give a flavour of the credit risk of a company, the simulation displays the most-after-due-date exposure.

For the sake of the simulation, the priority of the repayments is solely determined by the date of origination of each and every liability. No effects interest rate changes on the debt nor strategic importance of the relationship or bargaining power of a supplier will

[6] $O_{t-1,i-1} - Q_{t-1,i} - O_{t-1,i} + O_{t-1,i-1} - W$
[7] Price mark-up, warehousing unitary cost, % fixed cost
[8] Besides Payment-in-kind (PIK), not considered here.
[9] The expected payable deadline.

be considered.

Chapter 14

Descriptive Analysis

Training and testing sample are generated by repeatedly triggering different conditions in the supply chain to simulate different levels of average operational distress. The distress is induced in the 2nd 3rd and 4th tiers. The monitored company is at tier 3. Since there is not a clear-cut definition of operational distress in real life, we provide here a mathematical definition of it, according to our model parameters, that is, at each level i and for every time span $\Delta_{t_1-t_0}$:

$$D \equiv \frac{\sum_{t_0}^{t_1} a_{\mathrm{MAX}} - a_t}{\Delta t \times a_{\mathrm{MAX}}}$$

Where $a_{\mathrm{MAX},i}$ is the maximum production rate at each level, and $a_{t,i}$ is the actual production rate, as defined. By definition, $D \in [0,1]$ High levels of distress correspond to values of D closer to 1. Conversely, $D \simeq 0$ characterise well performing companies. Note that D does not depend on the size of the enterprise, nor from the interaction of enterprises.

14.1 Data Visualization

The four diagrams in table 14.1 display the net cash[1] of companies in the 3rd tier, in three distinctly simulated scenarios. 1st and 2nd quadrants (from top left, clockwise) refer to scenario 1, the 3rd quadrant refers to scenario 2 and the 4th quadrant denotes scenario 3.

Table 14.1: Operational distress

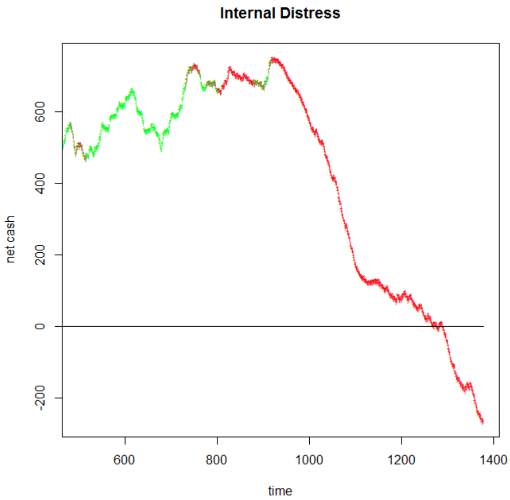
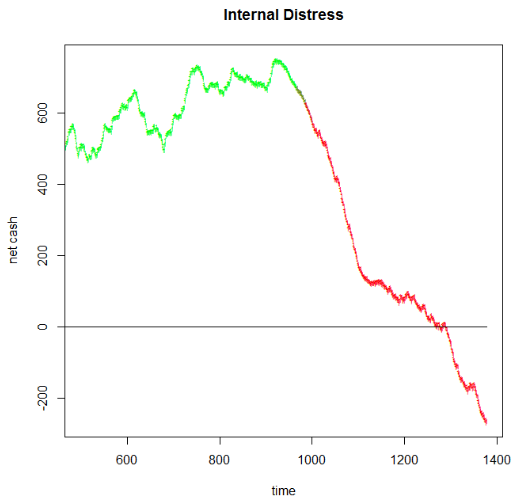
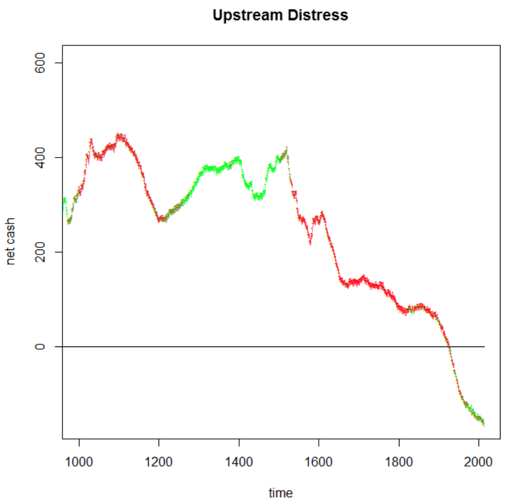
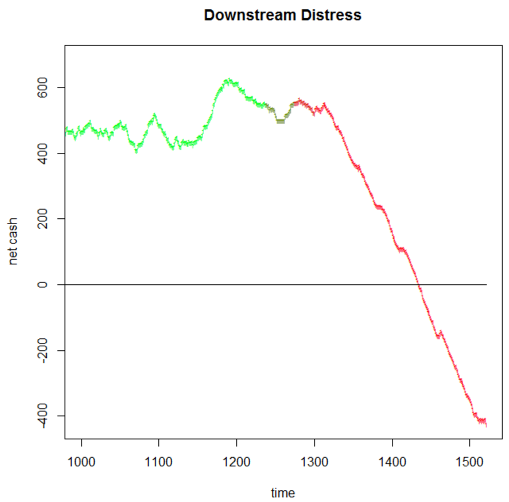
	Tier 1	**Tier 2**	**Tier 3**	**Tier 4**	**Tier 5**
Scenario 1	1.0%	1.4%	**40.5%**	18.6%	1.9%
Scenario 2	6.7%	**40.9%**	5.3%	1.3%	3.1%
Scenario 3	1.6%	5.4%	9.1%	**29.4%**	0.9%

By triggering distress along different tiers of the simulated supply chains, we empirically observe how, to the deterioration of CRF, (on the graph highlighted in red) corresponds a decrease in net cash. In the table is represented the level of distress along the supply chain as it has been defined before. As mentioned, the first two

[1] $\sum$ Cash Inflows $-$ $\sum$ Cash Outflows

quadrants display the same situation. Notice how early signal of liability are detected by the timeliness CRF, while VAT frequency CRF is triggered slightly later in time. The difference consists in circa 50-100 simulation periods. For this reason, timeliness CRF is supposed to be more forward looking than VAT frequency. Likewise, distress from up/downstream in the supply chain (as displayed in the 3rd and 4th quadrants) seems correlated with worsening of net cash situation. In all the scenarios, CRFs are triggered approximately 400 periods early that the defaulting condition is reached. However, besides visual evidence of the correlation between CRFs and the worsening of the creditworthiness, the purpose is to statistically set such alleged evidence.

Table 14.2: Evidences of CRF deterioration in stressed scenarios

	CRF = *Timeliness*	CRF = *VAT Frequency*
Internal CRFs		
Network CRFs		

Chapter 15

Quantitative Analysis

15.1 Stand-Alone Significance of CRF

Prior to the development of the model, we want to test the individual predictive capacity of the selected CRFs, to statistically corroborate the empirical observation in the previous paragraph. Individually, the significance of each predictor is tested by fitting a logistic regression model, at different time lags. In synthesis, all the variable are statistically significant with 99.9% confidence up to 12-month lag.

Table 15.1: Significance codes

p-value	**Code**	**Significance**
< 0.001	***	Very high
< 0.01	**	High
< 0.05	*	Acceptable
< 0.1	.	Low
> 0.1		No

15.1.1 Internal CRF: Timeliness

Table 15.2: Timeliness significance

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-1.06881	0.16579	-6.447	1.14e-10	***
Timeliness @365	0.15513	0.03041	5.101	3.38e-07	***

In table 15.2, we report the detailed output of the model for the 12-month lag. Table 15.3 reports the p-values listed for the other lags. Significance is confirmed up to the 12-month lag, coherently with the graphical observation. The correlation is, in any case, positive, which confirms *H1*.

Table 15.3: Timeliness significance

Lag	3-months	6-months	9-months	12-months	18 or greater
p-value	1.59e-08	2.98e-08	6.99e-08	3.38e-07	> 0.1
Significance	***	***	***	***	

15.1.2 Internal CRF: VAT Frequency

Table 15.4: VAT frequency significance

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-0.7822	0.1418	-5.516	3.47e-08	***
Δ VAT @365	18.2413	4.9182	3.709	0.000208	***

In table 15.4, we report the detailed output of the model for the 12-month lag. Table 15.5 reports the p-values listed for the other lags. Significance is confirmed up to the 12-month lag, coherently with the graphical observation. The correlation is, in any case, positive, which confirms *H2*.

Table 15.5: VAT frequency significance

Lag	3-months	6-months	9-months	12-months	18 or greater
p-value	2.96e-06	5.60e-06	1.59e-05	0.000208	> 0.1
Significance	***	***	***	***	

15.1.3 Network CRF: Timeliness

Table 15.6: Timeliness significance

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-1.33235	0.19314	-6.898	5.26e-12	***
Up. Timeliness @365	0.08214	0.01363	6.026	1.68e-09	***

In table 15.6, we report the detailed output of the model for the 12-month lag. Below, the p-values listed for the other lags. Significance is confirmed up to the 12-month lag, coherently with the graphical observation. The correlation is, in any case, positive, which confirms *H3*.

Table 15.7: Timeliness significance

Lag	3-months	6-months	9-months	12-months	18 or greater
p-value	1.48e-08	2.99e-07	1.46e-08	1.68e-09	> 0.1
Significance	***	***	***	***	

15.1.4 Network CRF: VAT Frequency

Table 15.8: VAT frequency significance

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-0.6944	0.1367	-5.078	3.82e-07	***
Down. Δ VAT @365	4.8272	1.3882	3.477	0.000506	***

In table 15.7, we report the detailed output of the model for the 12-month lag. Table 15.7 reports the p-values listed for the other lags. Significance is confirmed up to the 12-month lag, coherently with the graphical observation. The correlation is, in any case, positive, which confirms *H4*.

Table 15.9: VAT frequency significance

Lag	3-months	6-months	9-months	12-months	18-months	Greater
p-value	0.000566	0.000577	0.000566	0.000506	0.138	> 0.1
Significance	***	***	***	***	*	

15.2 Collinearity

As anticipated, the CRFs are being tested with different time lags from the defaulting threshold, from 3 months to 3 years. Following, the results of model fitting are reported extensively for the 12-month time lag only, while synthetically presented for the others lags.

The first step in the analysis in to check for possible correlation among CRFs. The model should indeed not take into account variables that explain the same effect. According to the scatterplot matrix, in figure 15.1 the two internal CRFs appear to be covariate. Nevertheless, as the relation appears to be not quite linear and the correlation coefficient is < 0.8, we will test the two variables in the first iteration of the logistic regression. No other significant pairwise correlation is worth noticing.

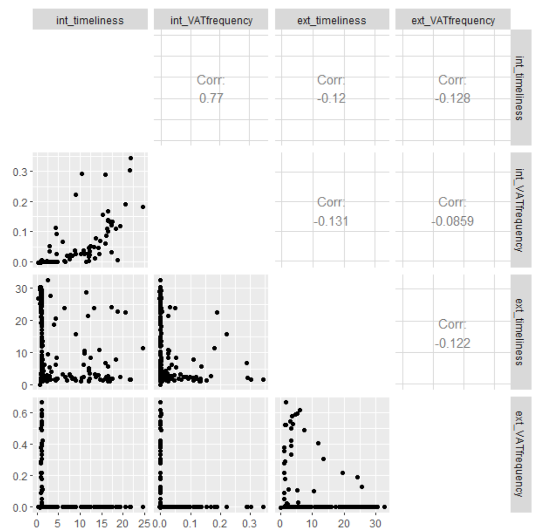


Figure 15.1: CRFs scatterplot

Table 15.10: CRF significance

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.48803	0.42016	-8.302	$<$ 2e-16	***
Timeliness @365	0.24865	0.05976	4.161	3.17e-05	***
Δ VAT @365	7.45804	7.21262	1.034	0.301	
Up. Timeliness @365	0.14620	0.01897	7.707	1.29e-14	***
Down. $\boldsymbol{\Delta}$ VAT @365	9.62113	1.77099	5.433	5.55e-08	***

As the underlying linear regression is fitted, it clearly appears that the internal CRF VAT frequency does not add explanatory power to the model, therefore the model is fitted again without the non-relevant variable. At any rate, all the variables are positively correlated, which confirms *H1*, *H2*, *H3* and *H4*, for the 12 months lag.

Chapter 16

Logit Classification

16.1 Results

All the CRFs are now contributing with statistical significance to the model.

Table 16.1: Transaction based model — Logit regression

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.54062	0.41856	-8.459	$< 2e\text{-}16$	***
Timeliness @365	0.29424	0.04344	6.773	1.26e-11	***
Up. Timeliness @365	0.14596	0.01901	7.677	1.63e-14	***
Down. Δ VAT @365	9.64486	1.77217	5.442	5.26e-08	***

The intercept term does not have a physical meaning, but it is needed, for a couple of reasons. Primarily, the dataset is slightly unbalanced towards peach borrowers: meaning that, among the generated scenarios, slightly more than the 60% of the sample data belongs to the non-defaulting category. Secondly, the intercept is consequence of the fact that not all the predictors can assume zero value. In fact, timeliness is measured here as Production Lead Time (PLT). In our framework, as mentioned, we assume that all the orders take approximately the same amount of time to be produced, as they are of similar size and there is only one production factor involved (refer to chapter 13), that is to say timeliness, as it is defined, differs from PLT by a constant term, which by the way does not introduce any sort of bias the predictive capability. We then run an ANOVA test. The difference between the null deviance and the residual deviance shows how the model is better preforming against the null model (a model with only the intercept).

Table 16.2: Analysis of Deviance

Coefficient	dof	Deviance	Res. dof	Res. Deviance	p-value	
NULL			261	345.36		
Timeliness @365	1	34.455	260	310.90	4.362e-09	***
Up. Timeliness @365	1	58.773	259	252.13	1.769e-14	***
Down. Δ VAT @365	1	50.021	258	202.11	1.521e-12	***

All the variable significantly contributes to improve the reduce the residual variance of the null model. Testing the model yields an accuracy level of 87%. Accuracy is calculated from the confusion matrix as:

$$A = \frac{\text{True Positive} + \text{True Negative}}{\text{Observations in Test Sample}} = \frac{39 + 16}{63}$$

. Since the number of good and bad performers do not equal, the cut-off for has been set accordingly, to reflect this imbalance in the error terms, as previously in chapter 12. We calculate this threshold as

$$C = \frac{\text{Default in Train Sample}}{\text{Observation in Train Sample}} \sim 0.37$$

, in order to proportionally (i.e. with respect to the ratio of lemon and peaches in the testing sample), maximize the sensitivity and specificity. Sensitivity, in our case, defines the capability of the model to correctly classify a borrower as defaulting (true positive), while specificity refers to the goodness in labelling the fewest possible peaches as belonging to the lemon category. Consequently, two types of errors are defined. First-type error, α, is the probability that the model will classify a lemon borrower as performing, while β, alias type-2 error, is the likelihood that the model would categorize a company who deserves a loan, as if it would not.

Table 16.3: Transaction based model — Confusion matrix

		Actual	
		Peaches	*Lemons*
Predicted	*Peaches*	39	2
	Lemons	6	16

It is important to highlight that this value does not reflect by any means the actual ratio of defaulting/non-defaulting companies, but exclusively refers to their proportion in the training sample. Below, the Receiver Operating Characteristic (ROC) curve and the sigmoid-like logit function of the model.

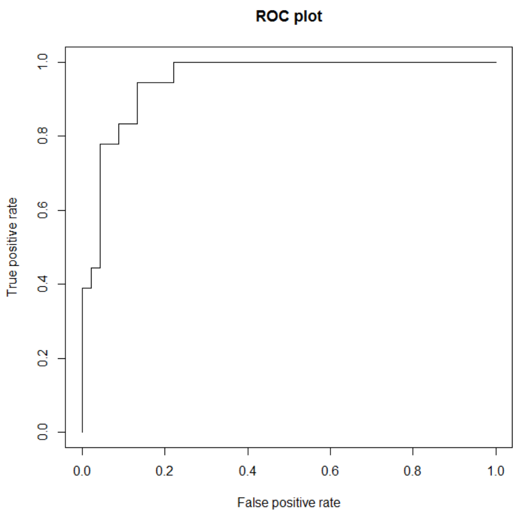


Figure 16.1: AUC $\sim$ 95%

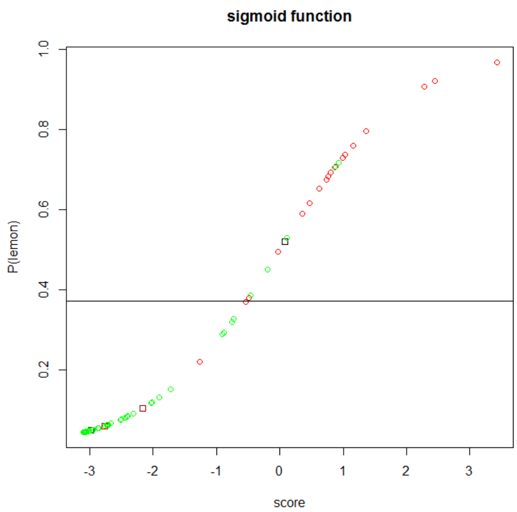


Figure 16.2: Cut-off $\sim$ 95%

The ROC plot allows to compare the predictive capabilities of binary classification models. Specifically, it displays the trade-off between first (α) and second-type error (β), in the form of true and false positive rate. The vertical axes plots $(1-\alpha)$, i.e. the sensitivity of the test, while the abscissae directly display the β error. The bisector line of the graph represents a test without any diagnostic benefit, while upwards convexity, as for in our case, is a sign of a good model. Ideally, we would like a classifier that identifies all the critical borrowers, but inevitably increasing the sensitivity brings to a misclassification of some good performers as lemons. Our model is fairly good, though. A sensitivity of more than 90% brings to misclassify less than 20% of the peaches. Of course this can be triggered, by changing the threshold as we did just above. As we do not have any reason to ”prefer” any of the two error situations,[1] we go for a model that minimize the trade-off between these.

Likewise, the sigmoid function shows that the model allows to discriminate lemon performers (in red), which predominantly lay above the cut-off, from peaches (in green). The squared dots represent those entities who did not actually trespassed the defaulting threshold but that, at the end of the simulation, were in bank overdraft and had a variable number of day past due between zero and eighty-nine. The reddish the square is, the closest the company is to the threshold, and vice versa. For those entities, the model is not as effective, as it was fitted on the 90-days threshold.

16.2 Other Lags

16.2.1 3 Months

Table 16.4: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.34618	0.42823	-7.814	5.54e-15	***
Timeliness @92	0.04268	0.06909	0.618	0.5367	
Δ VAT @92	14.91448	6.22271	2.397	0.0165	*
Up. Timeliness @92	0.14860	0.01963	7.570	3.75e-14	***
Down. Δ **VAT @92**	9.45291	1.75009	5.401	6.61e-08	***

As the underlying linear regression is fitted, it clearly appears that the internal CRF timeliness does not add explanatory power to the model, therefore the model is fitted again without the non-relevant variable. At any rate, all the variables are positively correlated, which confirms *H1*, *H2*, *H3* and *H4* for the 3-months lag.

Table 16.5: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.24588	0.38824	-8.360	$< 2e\text{-}16$	***
Δ VAT @92	18.39934	3.23691	5.684	1.31e-08	***

[1] β error is often perceived as the most relevant. The rationale is that, though we might tolerate not to be able to reckon a lemon (i.e. α error) as it normally happens, while there is a moral question (a missed opportunity for the lender), in setting up an overly sensitive test that reduces the overall number of companies that can access to financing because of high false positives. This might appear clearer if considering a diagnostic test for a disease. Despite being acceptable not to be able to recognize an early symptom of cancer, it is unacceptable to prescribe a chemotherapy to a healthy individual.

Up. Timeliness @365	0.14860	0.01963	7.570	3.75e-14	***
Down. **Δ** VAT @365	9.33278	1.72676	5.405	6.49e-08	***

Table 16.6: Analysis of deviance at 3 months

Coefficient	dof	Deviance	Res. dof	Res. Deviance	p-value	
NULL			261	345.36		
Δ VAT @183	1	54.206	260	291.15	1.805e-13	***
Up. Timeliness @183	1	58.500	259	232.65	2.033e-14	***
Down. Δ VAT @183	1	49.900	258	182.75 1.618e-12	***	

16.2.2 6 Months

Table 16.7: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-2.79390	0.34963	-7.991	1.34e-15	***
Timeliness @183	0.03749	0.06180	0.607	0.544	
Δ VAT @183	20.37930	7.55650	2.697	0.007	**
Up. Timeliness @183	0.11376	0.01604	7.090	1.34e-12	***
Down. Δ VAT @183	8.49861	1.62406	5.233	1.67e-07	***

Analogously, as the underlying 6-month-lagged linear regression is fitted, that the internal CRF timeliness does not add explanatory power to the model, therefore the model is fitted again without the non-relevant variable. At any rate, all the variables are positively correlated, which confirms *H1*, *H2*, *H3* and *H4*, for the 6-months lag.

Table 16.8: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-2.71657	0.32159	-8.447	$< 2e-16$	***
Δ VAT @183	24.29231	4.28816	5.665	1.47e-08	**
Up. Timeliness @183	0.11324	0.01595	7.098	1.26e-12	***
Down. Δ VAT @183	8.40545	1.60957	5.222	1.77e-07	***

Table 16.9: Analysis of deviance at 6 months

Coefficient	dof	Deviance	Res. dof	Res. Deviance	p-value	
NULL			261	345.36		
Δ VAT @183	1	50.917	260	294.44	9.635e-13	***
Up. Timeliness @183	1	47.338	259	247.10	5.973e-12	***
Down. Δ VAT @183	1	44.440	258	202.66	2.623e-11	***

16.2.3 9 Months

Table 16.10: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.26483	0.40129	-8.136	4.09e-16	***
Timeliness @274	0.11292	0.06209	1.819	0.0690	.
Δ VAT @274	20.18410	8.70763	2.318	0.0205	*
Up. Timeliness @274	0.14193	0.01886	7.524	5.31e-14	***
Down. Δ VAT @274	9.15770	1.70982	5.356	8.51e-08	***

Again, fitting the linear model again all four the predictors, shows that the internal CRF timeliness does not add explanatory power to the model, therefore the model is fitted again without the non-relevant variable. At any rate, all the variables are positively correlated, which confirms *H1*, *H2*, *H3* and *H4*, for the 9-months lag.

Table 16.11: Logit @ 3 months

Coefficient	Estimate	Std.Error	Z	p-value	
Intercept	-3.0150	0.3607	-8.359	$<$ 2e-16	***
Δ VAT @274	34.3193	6.1155	5.612	2.00e-08	***
Up. Timeliness @274	0.1397	0.0184	7.593	3.12e-14	***
Down. Δ VAT @274	8.8257	1.6736	5.273	1.34e-07	***

Table 16.12: Analysis of deviance at 9 months

Coefficient	dof	Deviance	Res. dof	Res. Deviance	p-value	
NULL			261	345.36		
Δ VAT @274	1	41.849	260	303.51	9.862e-11	***
Up. Timeliness @274	1	56.462	259	247.05	5.728e-14	***
Down. Δ VAT @274	1	46.301	258	200.74	1.014e-11	***

16.3 Overview

As a synthesis, we report the outputs of the fitting of the logit model for lag others that 12-month.

Table 16.13: Transaction based model — Logit regression summary

Time Lag	**Statistically-significant CRFs**[2]	**Accuracy**	**AUC**
3 months	*H2*, *H3*, *H4*	87.3%	0.958
6 months	*H2*, *H3*, *H4*	87.3%	0.975
9 months	*H2*, *H3*, *H4*	85.7%	0.932
12 months	*H1*, *H3*, *H4*	87.3%	0.952
18 months	*H1*, *H3*		

Within a one year-time span, the model performs well, between 12 and 18 months the model start to lose its predictive power. Overall, the analysis confirms *H5*, for time lag narrower than one year and a half, coherently with what observed while testing the individual significance of the predictors. It is worthwhile to notice that the forward-looking attitude of the timeliness as credit risk factor is statistically confirmed, as *H1* is more significant that *H2* in for the 12 and 18-months lags. Eventually, the model loses its predictive capability between 12 and 18 months, i.e. around 400 simulation periods earlier than the defaulting situation, as guessed by the qualitative analysis at the beginning of this chapter.

[2] P-value > 0.99

Part V

NOWC Based Model

Chapter 17

Credit Risk Factors

As highlighted in chapter 6, parametric model cannot leverage large datasets. The number of parameters is cannot vary according to the dataset on which the model is fitted. Non parametric model allows to release this assumption and, with due precautions to avoid overfitting, they potentially enable to capture more information from the data. For these purposes, we have access to a large repository of corporate data for public and private companies across Europe.

17.1 Net Operating Working Capital

A recent survey of European CRAs [74] defines twenty-four sub-factors from the value chain that are incorporated, to different extents, in the rating assessment. These determinants aim at analysing structures, processes and performances of the SC and how their impacts on the business performance of the rated entity, but their final impact on the grade is rather low. NOWC is cornerstone parameter to measure the well-being of a company from the financial operational side. Indeed, NOWC is a measure strongly tangled with the cash-to-cash cycle, a measure bridging inbound material activities with suppliers, manufacturing operations, and outbound sales activities with customers [44]. In turn, a monitoring cash level of borrower is crucial for every credit institution, as most of the debt is paid back in cash. We already mentioned two other components

Starting from these consideration and coherently with the approach described in chapter 9, the model factors in three different variables, accountable for two different types of performances along the supply chain.

17.2 Internal Risk

A proper management of a firm asset is crucial within the supply chain context [95] [27] and operational leaness is of paramount importance for positive financial performances. Recent studies [13], showed how credit rating is related to inventory leaness in a concave relationship: if, on one hand, inventory is a buffer against uncertainty and should be minimized [98], on the other hand, zero inventory policies [55] are a mistake and should be avoided.

17.2.1 Inventory Turnover

In line with this perpective, Gartner publishes a yearly ranking of the best twenty-five supply chain leaders in supply chain performance and strategies. The ranking is based on qualitative experts' judgement and quantitative parameters and inventory turnover represent 10% of the overall mark. It seems therefore meaningful to include this variable in our model as a reliable proxy of operational leaness in the way proposed by [13].

17.3 Network Risk

Indeed, neglecting supply chain side is a huge drawback in the traditional credit risk approach. A comprehensive assessment of SMEs performance should consider that each enterprise in the SC contributes differently to the creation of value and that financial indicators as the efficiency of capital turnover or cash flows, strongly changes among small enterprises according to their junctions with the surrounding environment [61]. Credit chain and bankruptcy propagation Look at the SC network of an enterprise is of crucial importance. In a highly-tangled network of trade credits, the performances of the neighbouring nodes can strongly influence the focal firm, since financial difficulties of a firm will likely affect SC partners. If we consider the event of bankruptcy, the ultimate stage of a defaulting corporation, as the instance for which a company is no longer able to repay its debt, we might argue that detecting early signals and degree of dependence from companies at risk, might be useful for assessing, in turn, the risk of the focal company. The rationale is that, the safer is the environment in which an organisation operates, the lower is the risk of a domino effect of these contingencies. Under this perspective, value chain factors might play a crucial role from a predictive perspective. With regards to the SC network, we distinguish two different sources of bankruptcy [12]. The first kind is triggered by unexpected sudden increase of cost or decrease in revenue, i.e. when revenues become too low with respect of costs. The second one, occurs when a supplier at a certain level, is repeatedly not paid by one or more of its buyers. Said supplier, whose solvency capability has been hampered, could it turn not be able to pay its own suppliers, thus potentially triggering an avalanche of consecutive bankruptcies.

17.3.1 Days Payables and Receivables

Previous literature conjecture a link between trade credit and creditworthiness. This is meaningful, since supply chain partners should be those who are better able to assess the performances of their suppliers/customers. Extra information arises from the experience of the commercial relationship and it is justified by the interest of whatever actor to enter in trade with creditworthy and well performing partners. In turn, this extra information might be reflected by trade credit in two ways. On one hand, suppliers are willing to concede higher commercial credit to those partners they know that deserve this type of supply chain financing while, conversely, they wish to cash as soon as possible those exposures towards more doubtful companies. Therefore, suppliers might act as intermediaries between buyers and banks because they possess superior information [32] [67]. Trade credit may act as a screening device that elicits information about buyer default risk [89]. The optimal credit period decreases with the probability of default, and it is conjecture that the role of default risk is to determine whether to grant trade credit [88]. Late payment, i.e. settlement after due date, is common in firms that lack of cash to finance their operations: suppliers react to late payments by withholding further supplies [58]. It seems therefore meaningful, to deem companies with long payables days, to be more performing than the average, and vice versa . Conversely, an actor with larger receivables might indicate someone working in a well-established supply chain, where trust among players is a matter of fact . As shown in the above, a solid supply chain is crucial to survival, especially for smaller actors. On the contrary, if a company shows shorter-than average receivables, this might indicate that either that company do not trust its customers or, that cannot afford to be paid in the normal times that suggested by common sense in commercial credit. One might argue that payables and receivables are due to the bargaining power of the parties . Negotiation strength might arise from either size or strategic position of one of the two actors in a trade. As our analysis deals with the SMEs world, we assume that a) size is relatively homogeneous among actors and therefore not a discriminant of bargaining power and that b) bargaining strength arising from strategic advantage is not relevant.

Chapter 18

Hypotheses

Particularly in the setting of a neural network, it is hard to assess the correlation with a variable with the output value. Given the repeated interactions among each input in the net, and the nature of the backpropagation process, a neural network is most like a black box where inputs are processed in a deterministic but unclear fashion. Therefore, when assessing the hypotheses, we could assume how a certain predictor would behave, since we would not be able to tell whether our hypothesis has been confirmed or not. In other words, in a linear parametric model, covariates, if significant, are either directly or inversely correlated with the output value. This cannot be clearly assessed in presence of non-linear and complex models. Instead, and that is what we are doing, we can assess whether a certain variable exert an impact on the overall predictive capacity of the model, by monitoring ad-hoc accuracy statistics. In our setting, we want to assess the predictive capabilities of the three abovementioned predictors:

- period (days payables),
- collection period (days receivables) and
- inventory turnover.

We claim that, coherently with what conjectured by [88], and [47] and in line with *RQ1*, these covariates could elicit hidden information about supply chain perceived creditworthiness.

Chapter 19

Descriptive Analysis

The problem is visibly nonlinear and the two classes, here in 19.1 highlighted in red (defaulting sample) and green (active companies), are not clearly separated. Regardless, we might notice the tencency for nondefaulting companies to cluster closer to the origin. This is an important observation corroborating both [89] wich discuss the tendency for companies in financial difficulties to strive for longer credit period, and [58], who observed positive relationship between habitual late payment and difficulty obtaining bank finance (which is directly related to creditworthiness). For better presenting the population, in 19.2 and 19.3 we show a few excerpts from the plot of the data along the three features, predictors are plotted on a log scale to better show differences in smaller values. There is a clear clustering tendency, but the border among the classes is rather blurred and definitely non-linear.

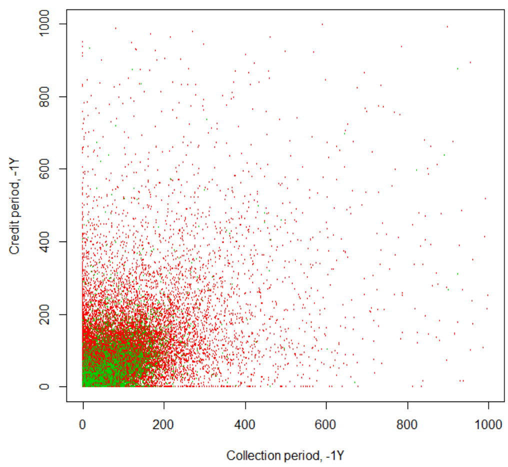


Figure 19.1: Distribution of company data

Before processing, a data normalisation is carried on, that is, each data point is rescaled in the interval [0,1]. Normalisation, due to account the significant order of magnitude in the data, is a common procedure in data analysis. It is required to eliminate potential biases arising by different dimensionality of the data, which might give undue importance to some parameters and neglect others simply due to a difference in their order of magnitude. Normalising proved itself to be a valid workaround to boost the performance of the classification model.

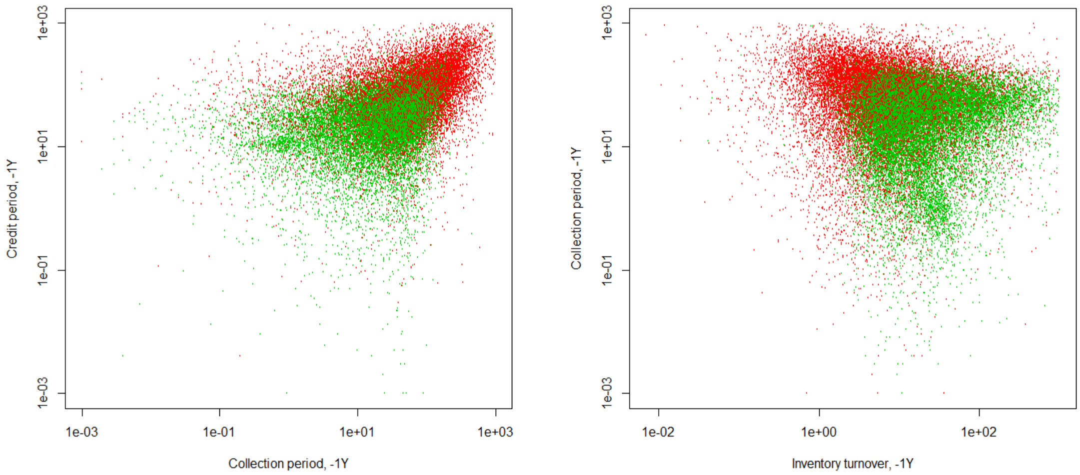


Figure 19.2: Distributions of company data (log scale).

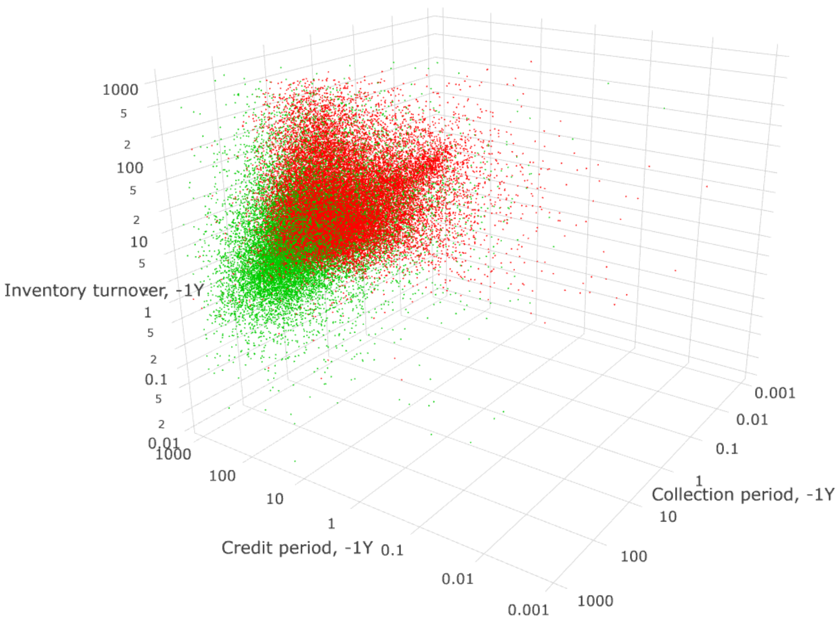


Figure 19.3: 3d distribution of company data (log scale).

Chapter 20

Quantitative Analysis

20.1 Multilayer Perceptron

The selected model is a multilayer perceptron, a topology of the neural networks class. As shown in the previous paragraph, the relationship among predictors in not linear, thus a traditional linear model, like the ones introduced above, would not suitable for the current classification problem. Instead, neural networks, as highlighted beforehand, introduce the ability to model nonlinearities and they seems more appropriated to the requested task.

This is not the first attempt of leveraging neural networks to assess creditworthiness. Nevertheless, works of previous scholars predominantly focused on the retail-side of the issue. This works, conversely, aims in analysing wholesale creditworthiness, with – as mentioned – a focus on SMEs.

Despite existing some works that suggest random search [14] and Bayesian Optimisation approaches for the definition of the hyperparameter for deep learning [90], manual tuning[1] it is widely used in literature, especially for classification problems where the structure is relatively simple and/or known [97]. These brute force-like methods, formally developed into the so-called technique of grid search reduce the hyperparameter choice to a finite combination, which is then tested and evaluated.

In our case, after some attempts, we observed that, working with a network of 12 inputs, 50 and 25 nodes per layer along 2 fully-connected[2] layers were the minimum requirement to allow the optimisation problem to account of the multiple facets of the interactions of parameters in the network. Adding more layers of nodes did not improve our results, less nodes, produced unsatisfactory learning speed and accuracy level. The weights in the arc that in the biases are initialised with values sampled form a truncated normal distribution.[3]

Table 20.1: MLP Hyperparameters

No. layers	2
Nodes	50, first layer, 25, second layer

[1] Arbitrary selection of the number of hyperparameter

[2] Fully-connectedness is a topological condition of a multilayer perceptron, for which, in every layer, each node receives in input every output of the previous layers. Eventually the backpropagation process defines the weights of each arc, setting the to zero, should any connection be non-relevant.

[3] $\mathcal{N} \sim (\mu, \sigma)$ shaped distribution, whose event space is bounded

Connection type	Fully connected layers
Activation function	ReLU
Dropout rate	97%, at the end of each layer
Output layer	Softmax
Optimizer	Adam algorithm

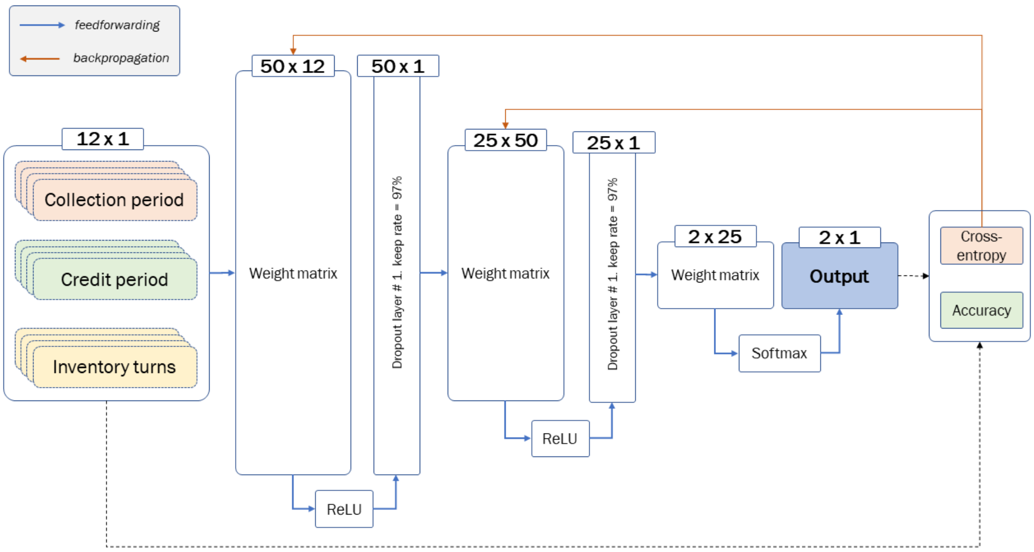


Figure 20.1: Multilayer perceptron structure

Figure 20.1 graphically illustrate the structure of the multilayer perceptron. The blue lines represent the feedforwarding flow for propagating the input along the network, while the orange arrows identify the paths backpropagation process. Data preparation and pre-processing, as well as the model training have been coded in the `R` language, with the support of the Tensorflow[4] API provided by RStudio[5]. For the actual code, please *see Appendix I*

[4]Open source architecture for machine learning, developed by the Google-owned company DeepMind
[5]Open source Integrated Development Environment (IDE) primarily developed for `R` programming

Chapter 21

NNet Classification

21.1 Model Training

As mentioned, the training process consists in processing the training input data in the network and running an optimisation of the hyperparameters (feedforwarding and backpropagation). These two action defines an an iteration. The training sample is divided in random batches of 5,000 companies. This is a common procedure when dealing with large datasets, for computational constraints due to available Random Access Memory (RAM). We define an epoch[1] as the number of iteration in a batch. We train the model along 5,000 epochs. Iteration are interrupted when the incremental improvement of the model training, due to new iterations becomes negligible.

Still, we need to perform some adjustments in order to take into account the unbalanced dataset. These are required to avoid biased results in the results. We face two choices, the first one, ex post, consist in measuring the goodness of the model with an unbiased estimator, the second, ex ante, requires to apply a fictitious balancing for training purposes.

21.2 Ex Post Adjustments

Accuracy is normally evaluated as $\frac{\mathrm{TP}+\mathrm{TN}}{\mathrm{P}+\mathrm{N}}$. This by assuming implicitly that the sample is evenly partitioned among its classes. In a real-world setting, this assumption is very often unacceptable. That is the reason for employing a different ratio called balanced accuracy. This ratio, described in [16] is defined as $0.5 \times (\frac{\mathrm{TP}}{\mathrm{P}} + \frac{\mathrm{TN}}{\mathrm{N}})$ which is, in other words, the average accuracy obtained on either class. It is a common practice to perform training on the 80 percent of sample data, while using the remaining 20 percent for testing purposes and so we did.

21.3 Ex Ante Adjustments

In this setting, both training and testing sample is created balanced. The training sample is recreated at every feedforwarding iteration, by keeping the smaller class while randomly sampling the bigger to the size of the other, before starting the feedforwarding. This way, the training sample is slightly different at every iteration, but the model still learns from

[1]Some defines an epoch as the number of iterations required to process the entire dataset.

a balanced dataset. This Standard accuracy metrics are enough if ex ante adjustments are performed. Being the testing sample artificially constructed, it is slightly differently sized. Namely, we want to as much as possible to preserve the balance 80 – 20, thus we randomly select 5,000 defaulted and 5,000 active from the $\simeq$ 50,000 companies. This way our testing sample is both balanced and represents approximately 1/5 of the data.

21.4 Results

We perform both approaches, in either case with comparable results, i.e. with difference in output orders of magnitude lower than the output accuracy. Learning can be either defined by the improved accuracy or by the reduction of the entropy of the model.[2] Both indicators are proxy of the goodness of the classifier. As noticeable form the Tensorboard export logs, referring to the training after ex-ante adjustments. The learning curve basically plateau approximately shortly after the 1,500th iteration. We then let the model training up to the 5,000th epoch to reasonably exclude any possible movements from the optimal minimum.

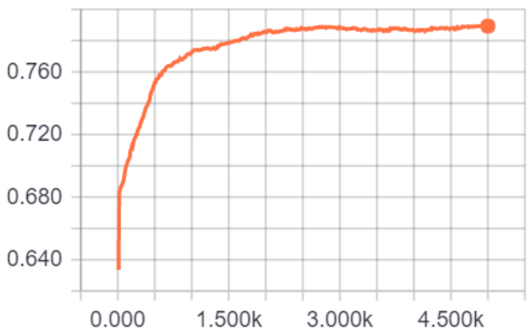


Figure 21.1: Accuracy

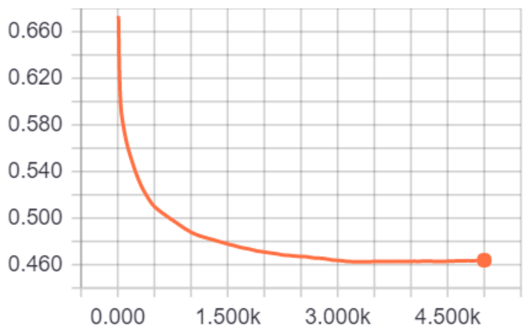


Figure 21.2: Cross Entropy (Error metric)

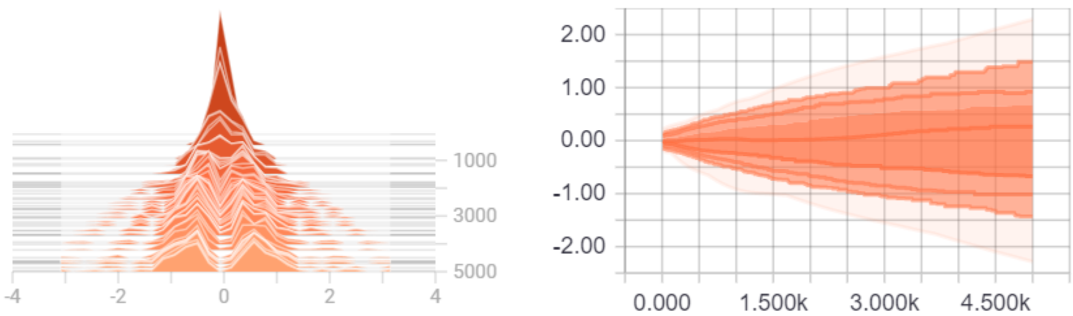


Figure 21.3: Output layer weights distribution

The model accuracy is 78.93%. Balanced accuracy is 78.93% as well. The graphs in 21.3, represent the evolution in time (i.e. along the number of training epochs) of the weights in the output layer weight matrix. From the background to the foreground (left graph) and for right to left (right graph), it is clearly noticeable how weights from their initialised values to a more scattered fashion. Such graphs allow to visualise the actual

[2]Defined as $\frac{1}{n}\sum \mathrm{TV}_i \times \log(\mathrm{G}_i)$, where TV_i is the i-th true value, $G_i \in [0,1]$ is the tuple output of the iteration of the model, and n is the number of observations in the training sample.

learning process of the network, which update itself to achieve better accuracy. Here below, the confusion matrix for the ex-ante adjusted training session.

Table 21.1: MLP Classifier — Sensitivity vs Specificity

Sensitivity $(1-\alpha)$	**Specificity** $(1-\beta)$
85.28%	72.58%

Table 21.2: MLP Classifier — Confusion matrix

		Actual	
		Active	*Default*
Predicted	*Active*	4,264	1,371
	Default	736	3,629
	Total	5,000	5,000

Out of the 10,000 training samples (5,000 active and 5,000 default), our model is able to correctly classify $\simeq$ 85 percent of the active sample and $\simeq$ 73 percent of the defaulting group. The lower accuracy in the classification of the defaulting companies relates to two relate facts. On one hand, there are fewer available data regarding defaulted assets. Unbalanced classed can be managed up to a certain extent, as explained above, but the model will learn to better classify those classes with higher variety and size. The second, and perhaps most important fact, is related to the goodness of the chosen predictors for classifying the companies. As noticeable from the plots in the previous chapter, the classes are not neatly separated. Even neural net can hardly overcome this problem. This is not a problem that can be eradicated only by increasing the sample size, but it must be tackled by increasing the dimensionality of the model, i.e. by introducing new predictors.

Chapter 22

Performance Appraisal

22.1 Increasing Sample Size

We further expand our analysis by increasing the size of the sample, which now records over two hundred thousands companies. The source and the characteristics of the sample are alike to the previous trial: the sample is an extension of the antecedent.

Table 22.1: Increased sample size

	No.	**%**
Active	178,729	84.0
Default	34,018	16.0
Total	212,747	

22.2 MLP Model

We train the model described in chapter 20 on the new sample, applying the same procedure. In table 22.2 we present the features of the newly trained model. Note how the model is slightly over-specific due to the larger non default sample, but the resampling helps the model in keeping the accuracy balanced.

Table 22.2: MLP classifier — Summary statistics

Statistic	**%**
Accuracy	75.52
Sensitivity	66.20
Specificity	77.30
Balanced Accuracy	71.75
Area Under Curve	79.36

A slight reduction of performance is expected since the sample is more than four times larger: a more than satisfying compromise for the increased generality of the model. In table 22.2 the confusion matrix and in figure 22.1 the plot of the receiver operating characteristic curve.

Table 22.3: MLP classifier — Confusion matrix

		Actual	
		Active	*Default*
Predicted	*Active*	20,716	1,728
	Default	6,084	3,385
	Total	26,800	5,113

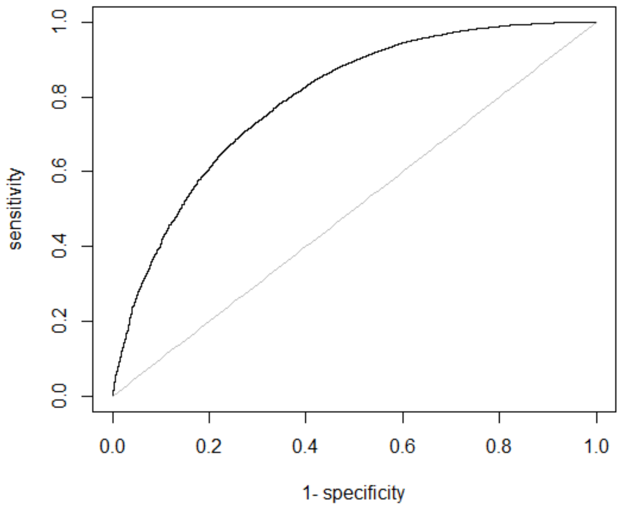


Figure 22.1: Multilayer perceptron — ROC Curve

22.3 Logistic Regression

We eventually fit a logistic regression model, as we did for the Transaction Based Model in chapter 16. Again, we randomly split training and testing sample on a 80:20 ratio and we fit a linear regression on the chosen predictors. Significance levels are as follows.

Table 22.4: NOWC based model — Logit regression

Coefficient	Estimate	Std.Error	Z	p-value	
	Estimate	Std. Error	Z p-value		
Intercept	2.1248	0.0111	191.450	¡ 2e-16	***
Credit Period t_0	-5.9540	0.1227	-48.538	¡ 2e-16	***
Credit Period t_{-1}	-0.2014	0.1490	-1.352	0.176421	
Credit Period t_{-2}	-0.9515	0.1507	-6.312	2.75e-10	***
Credit Period t_{-3}	-0.9134	0.1243	-7.351	1.97e-13	***
Collection Period t_0	-1.3901	0.1305	-10.653	¡ 2e-16	***
Collection Period t_{-1}	-0.7272	0.1643	-4.425	9.65e-06	***
Collection Period t_{-2}	-0.1077	0.1732	-0.622	0.534180	
Collection Period t_{-3}	2.4497	0.1587	15.439	¡ 2e-16	***
Inventory Turnover t_0	-0.6760	0.1196	-5.654	1.57e-08	***

Inventory Turnover t_{-1}	1.3940	0.1764	7.904	2.70e-15	***
Inventory Turnover t_{-2}	0.6190	0.1665	3.717	0.000201	***
Inventory Turnover t_{-3}	0.5012	0.1422	3.525	0.000423	***

In table 22.3 we present the features of the logistic regression model. Sensitivity is very low, and the model is not able to properly discriminate defaulting versus non defaulting companies. In table 22.3 the confusion matrix and in figure 22.2 the receiver operating characteristic curve.

Table 22.5: NOWC based model — Logit regression — Summary statistics

Statistic	**%**
Accuracy	58.91
Sensitivity	26.16
Specificity	65.16
Balanced Accuracy	45.65
Area Under Curve	62.89

Table 22.6: NOWC based model — Logit regression — Confusion Matrix

		Actual	
		Active	*Default*
Predicted	*Active*	17,462	3,776
	Default	9,338	1,337
	Total	26,800	5,113

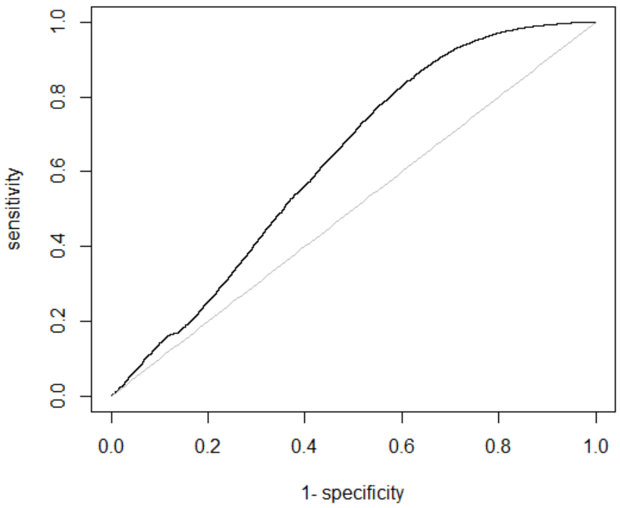


Figure 22.2: Multilayer perceptron — ROC Curve

22.4 Model Comparison

As conjectured in 6 and in chapter 9, we show how the the architecture of the multilayer perceptron achieves bettwe predicting performances on the larger sample, both in terms of sensitivity and specificity, increasing the area under curve of almost 20%, see figure 22.3 .

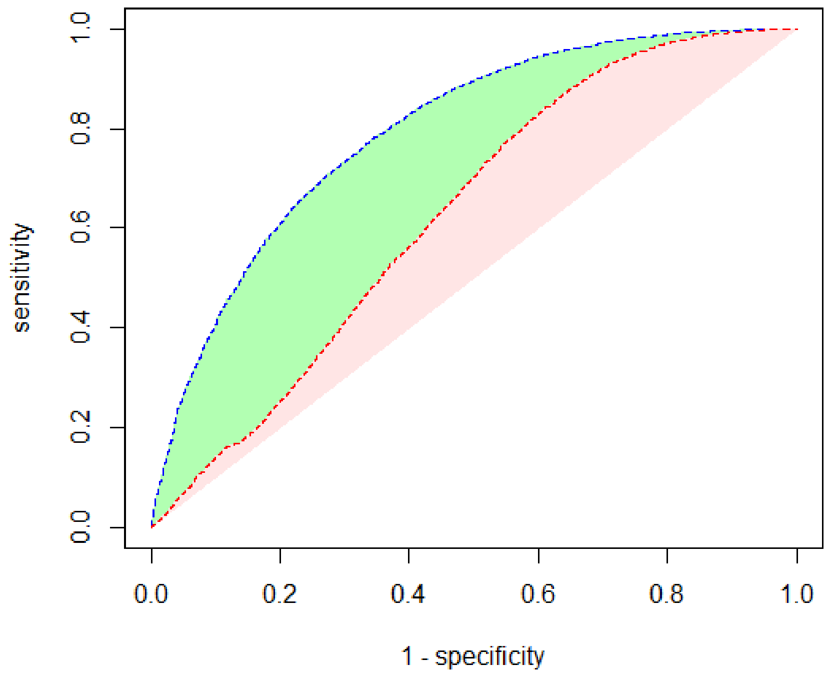


Figure 22.3: Comparison — ROC plots

The green-shaded area highlights the difference among the two models, being the blue-dashed line the Multilayer Perceptron (MLP) classifier. The red-shaded area represents the extent to which the logistic regression is able to outperform the so called ”coin-toss” - alias random - classifier. It can be visually seen how the MLP model well balances prediction on both classes, while the second model is incapable to correctly identify companies from the defaulting sample, which is visually noticeable as the red-dashed line quickly approaches the bisector line on the bottom left corner of the plot.

Part VI

Conclusions

Chapter 23

Findings

Overall, the scope of this dissertation was to provide a quantitative assessment of the potential performance of a supply chain-based rating model. On this premise, our work developed two models, whose common objective was to overcome the dichotomy financial performances-creditworthiness. Pros and the cons of these two approaches are better deepened in the following paragraphs, but, as a general remark, we could observe more than satisfactory performances. Due to the promising outcomes in the - though simplified - research environment, our results potentially have immediate (NOWC based model) application or short to mid term implementability (Transaction based model) in a real world setting. Plus, being based technologies whose application is exponentially growing, this methodological approach to creditworthiness assessment is definitely promising and worth of further investigation in the academic world.

23.1 Transaction Based Model

23.1.1 Hypotheses

Concerning *HP*s, all the CRFs are statistically relevant for discriminating bad and good performers in the simulated supply chain. As for the parsimonious model, the proposed internal CRFs are covariates. Interestingly, VAT frequency is statistically more relevant in the short term, while timeliness has a more long-term scope and it should be better for predicting on a longer horizon. This fact is coherent with the observation that operational distress can be earlier revealed as a lack of punctuality, and only in a second stage is explicitely manifested in term of missed payments. External CRFs are both statistically significant and are the proof that performance along the supply chain, can provide insights on the credit risk of the rated company, in line with [12], [80] and *RQ1*. Also, the model is reactive, as the CRFs can be potentially monitored on a daily basis, characteristic that could eventually settle the dilemma implied backwardness of financial-based models (*RQ2*).

Table 23.1: Hypotheses summary

Hypotheses	**Expected correlation with business failure**	**Confirmed**
H1	Positive	*YES* (though covariates)
H2	Positive	

H3	Positive	*YES*
H4	Positive	*YES*
H5		*YES*

23.1.2 Implications for Managers and Researchers

The works highlight the potential predictive power of non-financial risk factors with regards to the credit situation of a company, coherently with [72]. Moreover, measuring the CRF through transactional record comes at basically no additional cost, provided the ownership of transactional data. This should push researchers and practitioners towards a more careful consideration of this class of parameters, as they could potentially represent a pivotal point in the credit assessment technique for small businesses.

23.1.3 Limitation of the Study and Further Developments

Overall, the model is significant for the first 12-18 month, after which, the proposed CRFs lose their predictive significance. This might in part depend on the characteristic of the simulated supply chain. Considering different longer-term oriented CRFs may help in this sense. At any rate, detailed consideration related to the "forwardness" of CRF are hardly generalizable to a real-world setting. This - due on one hand to the multiple facets of different supply chains in diverse industries/countries and on the other, by the simplifications introduced by the modelling itself, or to better say, because of all those potentially relevant effects neglected by the numerical simulation - might alter the actual impact of CRFs on the creditworthiness of the rated company, perhaps diluting their effect on a different time frame, or vanishing in the grey noise engendered by other supply-chain phenomena.

As anticipated in the literature review chapter, the main drawback of the logistic regression is the bad inability to classify obligors over more than two classes, as it is instead required by the regulatory standards.

Masking Effect and Non-Linearity

The so-called masking effect, defines a situation where the linear regression[1] fails to separate the data, due to higher dimensionality of the problem, resulting in misclassification of the sample. More sophisticate models help overcoming the issue. For instance, it has been proven that linear discrimination models, under certain circumstances, are able to patch the issue [103]. To these regards, it has to be noticed that a significant issue persists with Linear Discriminant Analysis (LDA), and it is rooted in the definition itself of LDA: the linearity. The issue of linearity is a significant hurdle in a context where relationship between variables and output are everything but straightforward, especially outside a simulated environment. To these regards, linear regression, discriminant analysis, Bayesian panels, hazard model and most of parametric models can hardly overcome this issue.

[1] Which, let us remind that, is at the fundation of any logistic regression model.

Improvements

As mentioned, findings are based on a numerical simulation. This implies that necessarily numerous real-life credit risk factors might have been neglected. Also, the present analysis has been conducted triggering only a limited set of the simulation parameters. Further development might go in several directions:

1. More thoughtful analysis of the impact, on the credit situation of the entities, of changing currently fixed parameters in the simulation.

2. Development of the simulation engine including additional parameters to account for neglected effects. To mention two of them: multiple players in the same level of the SC and increase variability of the order size. Testing of different CRFs, as suggested from the literature (see table 23.2).

3. Empirical testing of the variables on real case situation to corroborate the model

4. Change of the underlying model to one capable to account both for multiple credit classes, in line with Basel requirements, as well as to define with the expected PD of the single obligor. To these regards, the approach of a nonparametric model might be well suited to the issue.

Table 23.2: Improvements

		Operational performances		
Name		**Metric**	**Source**	**Literature**
Quality	Upstr.		Vendor rating systems	[80]
Production pace	Upstr./ Downstr.	ΔTrans.Unity	Trans. unity/ Vendor rating system	[101]
		Transactional performances		
Name		**Metric**	**Source**	**Literature**
Amount of the principal	Downstr.		Trans. unity	[102]
Past due days	Downstr.	Current Date− Payback Date	Trans. unity	[102]
Past due amount	Downstr.	Principal Repaid− Principal Outstanding	Trans. unity	[102]
Outstanding amount	Downstr.	$\sum$ Principal Amount	Trans. unity	[101]

23.2 NOWC Model

23.2.1 Findings

Our analysis corroborated the conjecture [88] for which supply chain data, and especially payables and receivables days, may elicit information regarding creditworthiness. Likewise, we showed the that operarional leaness [13] can not only explain credit ratings, but - perhaps even more significantly - is directly related with the PD. This is a crucial leap forward with respect to traditional, financial-based credit risk evaluation [2], and strongly supports *RQ1*

One strength of the model we want to underline is its effectiveness on a rather heterogeneous data sample. SMEs sizes might span from € 50 m to € 5 m, which is a 10x difference in size. This, together with the fairly large dataset, which implicitly enhance the robustness and the generality of our findings, corroborates even more the consideration regarding the validity of the supply chain-based proposed predictors.

23.2.2 Implications for Managers and Researchers

The benefits of this work are two folded. On one hand, this model might be employed in the credit risk department of a bank, in support to traditional approaches. Banks have huge data repositories and they could easily develop their own classifier. Our approach is not standalone: 80% accuracy are not acceptable anywhere in the banking world. Hoverer, we noticed that including financial performances in the model significantly improved the capabilities of the model . As a matter of fact, our model allows an external observer to indirectly extract some – otherwise hidden – information from the supply chain. On the client side, a "certified" pre-trained model might be easily released for free so that obligors might have a better idea of which would be their creditworthiness from a bank perspective, thus increasing transparency in the process and in potentially reducing excessive bargaining discrepancies in the process of determining the borrowing rate.

On the research side, this work stress even more the importance of NOWC parameters in supply chain research and especially, as far as this article is concerned, in the field of supply chain finance. However, should someone like to infer academic guidelines information regarding the optimal value for the predictor, they might find hard times in doing so. This issue has been already mentioned in the hypotheses setting. Even being true the importance of the proposed predictors, quantitatively measurable through accuracy ratios, we stress the fact that the neural network, is a non-linear model. Which implies that it is capable to detect hidden relationship among variables. Hence, contrarily to a linear model, even if it is likely that extreme values would lead to bad performances and some kind of reverse engineering on the trained model could be attempted, it would be hard to define "the best" combination of supply chain parameters.

On the methodological side, the work presents an innovative - in a definitely underdeveloped landscape of solutions - application of neural networks and clearly show how - in this specific setting - they allow to better generalise and to extract additional information from only few predictors and on a strongly unbalanced sample, with respect to the well known, vastly used, logistic regression. This eventually enabled an $\tilde{2}0\%$ improved default recognition, according to Area Under Curve (AUC) metric. Said improvement is mainly due to the fact that MLP model maintains the balance between specificity and sensitivity even in case of highly uneven sample. This benefit is coherent with the expectations raised in chapter 12 regarding negative biases, and has potentially the chance to ease the access to credit to an increased number of companies.

23.2.3 Limitation of the Study and Further Developments

A key limitation of the current model, is that – at its current state of development – it is naively limited to the categorization of borrowers within two classes. Indeed, different level of creditworthiness are embedded in the non-defaulting class. As mentioned before, Basel regulation requires to categorize exposures within a minimum of seven classes. Such type of clustering might be achieved by means of other types of machine learning techniques, best suited for clustering data, such as K-Nearest Neighbours (KNN) or K-Means. Contrarily to multilayer perceptrons, these topologies falls within the category of unsupervised learning algorithm.

Further benefits will surely stem with more available computing power. All computations for this work were performed on a 64-bit, quad core processor at 2.3-2.4 GHz and 4 Gb of RAM.

A more thoughtful setting of multilayer perceptron hyperparameter, as indicated in the methodological section, would certainly improve the predictive capability of the model as well. Performances would likely improve with larger datasets, that might eventually enable separate training by industry sector or company size, thus likely improving performances. Lastly, since, trade credit it is also a matter of culture [31], it would be interesting as well to extend the sampling to different geographical contexts other than Europe.

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Part VII

Appendices

Appendix A

Classification of SCF Solutions

Classification of SCF solutions [20].

Table A.1: Classification of SCF solutions

	Solution	Description	Source(s)
Traditional Financing Solutions	Captive factoring	A typology of factoring in which the factor is owned by one large buyer and operates as its subsidiary, systematically purchasing all the invoices of the large buyer's suppliers, similar to reverse factoring. The close relationship between the captive factor and the buyer allows for an extreme credit risk reduction	[76]
	Reverse factoring	A typology of factoring in which the financial institution purchases the accounts receivables approved by specific, informationally transparent, high-quality buyers. The financial institution needs to calculate the credit risk of the selected buyers only, which is equal to the default risk of a high-quality customer, and not the risky suppliers (often SMEs). This arrangement provides low-risk financing to high-risk suppliers.	[68]

Innovative Financing Solutions	Advanced forms of reverse factoring	Technologically improved form of reverse factoring that allows the provision of capital to a higher number of suppliers at a lower rate, an increase in the quality and amount of information exchanged among partners and the involvement of new actors in the process, increasing the overall flexibility of the solution.	[87]
	Inventory financing	*Traditional*: short-term loan from a financial institution to finance inventories. *Innovative*: a logistics service provider buys goods from a manufacturer and obtains an interim legal ownership before selling them to the manufacturers' customers after a certain time	[53] [53]
	Dynamic discounting	ICT-based evolution of common trade credit policies; it allows the dynamic settlement of invoices in a buyer–supplier relation: for every day of payment in advance with respect to a pre-defined baseline, the supplier grants to the buyer a discount on the invoice's nominal value	[79]
	Seller-based invoice auction	Online marketplace where (usually) SMEs can auction their invoices to a group of investors, which compete in purchasing them.	[60]

Appendix B

Basel

B.1 Asset Classes

The five asset classes [7] are :

1. Corporate: debt obligation of a corporation, partnership, or proprietorship. Within this class, five further sub-classes of Specialized Lending (SL) are defined:

   (a) Project finance: a method of funding in which the lender looks primarily to the revenues generated by a single project, both as the source of repayment and as security for the exposure. This type of financing is usually for large, complex and expensive installations;

   (b) Object finance: method of funding the acquisition of physical assets, where the repayment of the exposure is dependent on the cash flows generated by the specific assets that have been financed and pledged or assigned to the lender;

   (c) Commodities finance: structured short-term lending to finance reserves, inventories, or receivables of exchange-traded commodities, where the exposure will be repaid from the proceeds of the sale of the commodity and the borrower has no independent capacity to repay the exposure;

   (d) Income-producing real estate: method of providing funding to real estate where the prospects for repayment and recovery on the exposure depend primarily on the cash flows generated by the asset.;

   (e) High-volatility commercial real estate: e financing of commercial real estate that exhibits higher loss rate volatility (i.e. higher asset correlation) compared to other types of SL;

2. Sovereign: all exposures to counterparties treated as sovereigns under the standardised approach;

3. Bank: mainly exposure to banks;

4. Retail: mainly exposure to individuals, residential mortgages;

5. Equity: direct and indirect ownership interests, whether voting or non-voting, in the assets and income of a commercial enterprise or of a financial institution.

B.2 Risk Weighted Assets

More specifically [8], [10], [75], risk-weighted assets:

$$\mathrm{RWA} = \frac{K(\mathrm{PD}, \mathrm{LDG}, \mathrm{M}) \times \mathrm{EAD}}{\mathrm{CAR}}$$

The capital adequacy ratio CAR, also known as capital to risk (weighted) assets ratio CRAR. Must remain above 8%:

$$\mathrm{CAR} \geq 8\%$$

Capital requirements (K):

$$\mathrm{K} = \left[\Phi\left(\frac{\Phi^{-1}(\mathrm{PD}) + \sqrt{\rho} \times \Phi^{-1}(0.999)}{\sqrt{1-\rho}}\right) \times \mathrm{LGD} - \mathrm{PD} \times \mathrm{LGD}\right] \times \mathrm{MA} \times \mathrm{SF}$$

Where:

- Φ is the Standard Normal distribution, and 0.999 is the supervisory-fixed confidence level: $\Phi = \mathcal{N}(0,1) = \mathrm{Z}$
- MA the maturity adjustment: $\mathrm{MA} = \frac{1+(\mathrm{M}-2.5)\times \mathrm{b}}{1-1.5\times \mathrm{b}}$, which includes the maturity adjustment smoothing factor (smoothing on PD): $\mathrm{b} = (0.11852 - 0.05478 \times \log(\mathrm{PD}))^2$
- SF is the scaling factor. It is simply a coefficient used by the regulator to make the formula more or less conservative. Currently, it is set to be 1.06. This must not be confused with SMEs supporting factors (0.7619) introduced in early 2014.
- The correlation coefficient ρ represent the extent to which the PD of the considered asset/exposure from a specific borrower depends on the other borrowers' assets/exposures, while $\sqrt{\rho}$ represent the correlation with the general economic context.

It is noteworthy to highlight the fact that the estimation of the correlation parameter does not reflect by any means the actual correlation of the asset in a given portfolio, being simply a plausible estimation of it, provided by the regulatory framework: $\rho = 0.24 - 0.12 \times \frac{1-\exp{-50\times\mathrm{PD}}}{1-\exp{-50}}$ note that, in case of SMEs (specific regulation for EU environment, this may change according to the definition of SME), whose turnover in the range [€5 million; €50 million], the correlation coefficient changes to:

$$\begin{cases} \rho - 0.4 \times \left(1 - \frac{S-5}{50}\right) & \text{if SME} > \text{€5 million} \\ 0.2 - 0.12 \times \frac{1-\exp{-50\times\mathrm{PD}}}{1-\exp{-50}} & \text{if SME} < \text{€5 million} \end{cases}$$

hence, the smaller the firm, the lower the (potential) correlation coefficient:

Table B.1: Correlation by turnover class

Annual Turnover	ρ
> €50 million	[0.12; 0.24]
> €5 million	[0.08; 0.24]
< €5 million	[0.08; 0.20]

Appendix C

List of European ECAIs

List of the registered European-resident ECAI and their corresponding market share based on turnover from credit rating activities and ancillary services updated at Dec 2015. [43]. Number of non-financial corporate rating outstanding at December 2015.[1]

Table C.1: List of European External Credit Assessment Institutions

Registered Credit Rating Agency	**Market share**	**SME rating**	**Corporate** *LT*	*ST*
AM Best Europe-Rating Services Ltd. (AMBERS)	0.93%	No.	47	
ARC Ratings, S.A.	0.03%	CLO.	5	5
ASSEKURATA Assekuranz Ratings-Agentur GmbH	0.21%	No.		
Axesor S.A.	0.61%	Yes.	62	
BCRA-Credit Rating Agency AD	0.02%	No.		
Capital Intelligence (Cyprus) Ltd.	0.14%	No.		
CERVED Group S.p.A.	0.88%	Yes.	19,489	
Creditreform Rating AG	0.50%	No.	66	
CRIF S.p.A.	0.05%	Yes.	34	
Dagong Europe Credit Rating Srl	0.04%	No.		
Egan Jones Ratings Company			172	
DBRS Ratings Limited	1.89%	CLO	14	1
Euler Hermes Rating GmbH	0.21%	Yes.	15	
European Rating Agency, a.s.	0.00%	No.		
EuroRating Sp. Zo.o.	0.01%	No.	15	
Feri EuroRating Services AG	0.40%	No.	2	
Fitch Group	16.56%	CLO	626	185
GBB-Rating Gesellschaft für Bonitätsbeurteilung GmbH	0.34%	Yes.		
ICAP Group SA	0.12%	No.	1,363	
Japan Credit Rating Agency, Ltd.			5	
INC Rating Sp. Zo.o.	0.00%	No.		
ModeFinance S.A.	0.05%	No.		
Moody's Group	31.29%	CLO.	854	233
Rating-Agentur Expert RA GmbH	0.00%	No.		
Scope Credit Rating GmbH	0.39%	CLO	17	

[1]Source: *CEREP*database.

Spread Research SAS	0.09%	No.	39	
Standard & Poor's Group	45.00%	CLO	1,060	380
The Economist Intelligence Unit Ltd.		No.		
Total	100%		23,885	804

Appendix D

ECAIs: Factors and Sub-factors considered

List of factor and sub-factor considered by European CRAs [80] [74].

Table D.1: Financial Factors

Profitability
Capital structure
Liquidity
Absolute values
Qualitative financial analysis

Table D.2: Non-financial Factors

Macroeconomic factors
Market conditions
Competitiveness
Strategy
Corporate governance
Value chain factors
Technology and R&D
Other operational factors
Risk
Group impact

Table D.3: Detail of non-financial factors

Description	*Sub-factor*	*Examples*
	Macroeconomic factors	
This factor incorporates aspects related to the environment in which companies operate. Such aspects are analysed with reference to the economic system at aggregate level, rather than focusing on a specific industry, and they are related to economic, legal, political, technological and financial conditions of the global environment.	Legal, political, economic and technological conditions	Strength of the national economy; legal, political and socio-economic climate; political and economic environment; unemployment; corruption at political level; inflationary trends; country risk & transfer and convertibility risk.
	Financial stability risk	Financial system risk; stable banking environment
	Market conditions	
This factor comprehends all features considered within the analysis of the industry in which the firm operates. More in detail, the sector is assessed not only in terms of its current situation, but also potential future changes and developments are accounted for.	Market trends	Trends in technological innovation, industry growth, Sector revenues prospects, trend in industry expansion
	Market structure	Level of business rivalry, markets entry and exits barriers, competitors behaviour, sector risk category, capital intensity, consolidation, maturity, degree of dependence on specific industries, level of regulation, supply and demand balances, drivers of competition and future degree of competition due to new market entrants, the current competitive situation
	Industry cycles	Cyclicality, pattern of the industry business cycle
	Economic, governmental and environmental issues	Impact of government on the industry, introduction of new regulatory decrees, regulation/environmental factors
	Competitiveness	

This factor refers to the ability and performance of a firm to sell and supply goods and services in a given market with respect to its competitors	Competitive position	Ranking; market share; market share trends; current competitive situation.
	Comparative cost position	Comparative cost position; cost profile referred to competitive advantage.
	Comparative cost position Sources of competitive advantages/ disadvantages	Strengths and/or weaknesses of the company relative to competitors; entity development in comparison to competitors; product differentiation, innovation and quality; brand strength; customer service; reputation; location; product portfolio and commitment to develop new products
	Geographic coverage	Customers geographic basis; geographic diversification; geographic mix; geographical spread of sales
	Strategy	
This factor includes the aspects referred to the company strategic objectives and orientation, as well as plans developed to achieve such goals. Moreover, considerations associated with the strategic plans implementation are here included too, since implementation cannot be assessed separately from the objectives. The aspects falling within this factor are for the majority assessed in a qualitative way, but some are appraised in quantitative terms.	Finance	Policies regarding medium- and long term plans; profit and loss plans; projected balance sheets and cash flow statements; compliance of strategic plans with business and financial plans; liquidity plans; spending policies; financing and investment plans; financial policies; ability to revise plans for capital spending; desired capital structure or targeted credit profile; share buyback activity; dividend policy
	Operationalisation	Policies and measures to achieve management goals; strategy implementation risks; historical performance of the firm against strategic goals; managerial structure and practices; business model.
	Diversification	Business segments; sales composition; products, customers, and sales channels diversification; revenues and clientele diversification; portfolio size; business mix and ability to create a healthy one;

	Capital investments	operating strategy; current and future status of overseas expansion; business diversity.
	Risk appetite	Risk appetite for spending decisions; organizational risk profile; management risk appetite.
	Growth strategies	Aggressiveness of future growth plans; funding requirement of new assets; M&A driven growth.
	Production strategies and other operational plans	Corporate Planning; frequency and coverage period of plans; quality of business planning
	Corporate governance	
This factor includes considerations related to the analysis of the organizational system (rules and practices) as well as the processes which support the maximization of the value of a company and based on which the entities are governed and directed.	Management	Capabilities, performance and stance of senior management; competencies of the management of the company; management achievements;
	Organisational structures and governance	Personnel resources; employees; structure created, practices and existing systems for management; personnel-related and performance-related relationships; organizational aspects; workforce expertise; availability and use of subcontractors and temporary workers.
	Ownership	Owners; ownership or shareholder structure; material changes in major shareholders stakes, in particular stake reductions; family ownership.
	Controlling instruments	Management of controllable risks; risk management; overall corporate structure; how are the strategy and objectives communicated within the organisation and how aligned are they within the organisational structure; degree of information disclosure; insurance coverage
	History	Years of operations; entity development over time; organisational history.

	Corporate culture	Relationship between management and labour; working conditions.
	Audit activities	Audit (presence and replacement); effective controls for integrity of accounting and audit; auditors comments in financial reports; interactions with outside auditors.
Value chain factors		
It relates to the analysis of the value chain structure, processes and performance and how it impacts on the business performance of the rated entity	Supplier/customer concentration	Risk concentration level; clientèle diversification
	Bargaining power	Contractual position; company negotiating position; pressure from clients and customers.
	Credit protection measures	Credit management; credit-protection measures.
	Vendor financing	Vendor financing
	Vertical integration	Risk associated with vertical integration; downstream Integration; degree of vertical integration.
	Relations with counterparts	Customer relations; strategic partners; considerations about the external support received from the concentrated producer; licensing relationships; sizable related-party transactions.
	Cost structure	Costs composition; capital and operating costs; material costs/total costs; operating cost structure
	Financial strength of key debtors and creditors	Credit rating of a counterpart with which the rated company has a significant exposure; financial health of suppliers; counterpart risk.
	Procurement	Procurement and sales conditions; purchasing policy.
	Production processes (service delivery)	Business processes; general and sector-specific core processes; business activities; key activities.
	Distribution	Efficiency of distribution network; distribution channels

	Risk from agreements	Risk of delivery shortfalls; risk which can arise from the agreements made and from the practices applied; payment behaviour; contract life
	Working capital management	Working capital management
	Inventory management	Inventory management
	Punctuality of payments	Punctuality of payments
	Amount of inventories	Amount of inventories; non-monetary working capital
	Production period	Production period
	Sales conditions	Business terms and conditions in contracts; setting up limits for business partners or country.
	Collection period	Receivable collection time; Days Sales Outstanding (DSO); receivables collection period.
	Payable period	Days Payable Outstanding (DPO); payables settlement period.
	Inventory turnover	Inventory storage period; inventory turnover; period of stock turnover from revenues.
	Operating cycle	Cash conversion cycle; operating cycle
	Changes in working capital items	Significant decrease/increase of receivables; significant decrease/increase of stock; % Change [Receivables from Customers (or payables to suppliers) / Bills and Cheques].
	Added value of products/services	Importance and relative value to customer; commodity versus value-added products; added value
	Technology and R&D	
	Technology level and R&D capabilities	Innovation of products; analysis of firm technology; technology level; ; vulnerability to drive technological displacement; technical positioning; R&D programs to complement, renew or replace products; originality of production methods; historical development organization and changes to its staffing

	Proportion of R&D expenses to sales	R&D expenses/sales
	Other operational factors	
This factor includes considerations about key processes and key structures which drive the overall organization towards the development of core operations. In particular, the effectiveness and efficiency with which the existing infrastructure supports the entity to the deployment of its core business are assessed within this factor. As already mentioned, one may tend to attribute the here included sub-factors into the value chain factor; however, it has been chosen to introduce on purpose this separate factor to distinguish between aspects referred to specific steps of the value chain (i.e. value chain sub-factors) and those associated with the overall use of the assets (i.e. other operational aspects sub-factors). In other words, this factor embodies aspects (mainly qualitative but also quantitative) that are transversal to the whole value chain	Efficiency and effectiveness of the existing capacity	Operating effectiveness; operating efficiency; asset quality; asset conditions and complexity; production efficiency; ability to maintain operating efficiency; Fleet management (for airline companies).
	Operational structure	Operating sites; operational structure; operational expertise; operational risk.
	Project management capabilities	Project management; company flexibility to change timing and scale of the project; project control (degree of formalization of processes and project risk assessment); project execution capabilities.
	Risk	

This factor embodies all risks the company is exposed to, not necessarily related to the business in which it operates and which cannot fall within the already discussed factors	Litigation risk	Type of delinquency; total value of delinquencies/Net Sales; number of delinquencies according to the type of data; year when delinquency occurred; % of settled delinquencies; legal disputes; lawsuits; regulatory actions against the company or its senior executives; litigation environment; number of certified class action claims pending.
	Assets and liabilities risks	Specific asset class risk; specific security risk; contingent liabilities and guarantees provided; piracy risk; patent exposures.
	Capability to meet compliance standards and requirements	Environmental issues; compliance standards and requirements; ability to meet high environmental specifications
	Applied accounting principles	Consistency in accounting policies and procedures; treatment of cash; approach to keeping accounting records; applied accounting principles; accounting risk; company ability to make adjustments to improve the liquidity position.
	Risk related to the workforce	Exposure to unionised labour market; delays due to strike actions; higher costs due to hostile labour relations; contingency planning against labour actions.
	Group Impact	
This factor refers to all considerations related to the company belonging to a group; in general, the overall group background is considered, as well as the position the rated entity occupies within the overall group; moreover, capital movements between group entities fall within this factors	Group background	Independent management; transfer agreements; cash pooling arrangements; ownership by a large group or a medium or small one; relationship between parents and their subsidiaries; degree of integration between the entities; group legal jurisdiction; parental support; group perimeter

	Affiliations	Provisions of loans, guarantees or bonds; affiliations; parent capacity and willingness to bail out the subsidiary under financial distress; explicit guarantees, letters of credit or other considerations by the parent; independence for funding purposes division/subsidiaries; provision of loans or leases to customers by financial subsidiaries to enhance the rated entity‘s sales; reliance on affiliates; guarantees or subsidies.

Appendix E

ECAIs: Methodologies for Structured Finance Rating

Description of European CRAs methodologies for SMEs credit risk evaluation for structured finance rating.

E.1 ARC Ratings CLOs Rating Criteria

The company does not possess any tailored method to rate SMEs. Where available, ARC employs proprietary rating of the underlying assets to infer a hypothetical default probability, however where an ARC rating is not available, the company will make reference to other CRAs judgement where available. Indeed, the company does not rate SME currently. ARC will only notch from these ratings if it considers it has a different view in respect of methodology applied to determine the ratings. If a rating is on negative outlook ARC may notch down one notch from the existing rating of other CRAs. Where no rating exists, ARC may perform a mapping of a bank's internal rating scale or accord a credit estimate or shadow rating, which may be an unpublished point-in-time opinion of the approximate credit quality of an individual security, financial contract, or issuer for which we have not assigned a rating. In order to maintain up-to-date credit estimates, the ARC requires that the manager regularly provide us with relevant information. In the absence of such information, we will not be able to maintain the credit estimate.

E.2 Creditreform Rating AG

The company claims to be Europe's leader in SMEs issue rating. Nevertheless, non e of the published document regarding structured finance methodologies or issue rating even mention SMEs at all.

E.3 DBRS Ratings Limited. Sample Operational Risk Agenda for European SME CLO Loan Servicers

No direct rating for SMEs. The CRA limits itself to the collection of average PD from the originators in of the CLO, and analyse the riskiness of the originator only. Here some of the parameters:

Table E.1: DBRS Rating — Collateralized Loan Obligations

Company and management	**Control and compliance**
Organisational structure, experience of the management and strategic plan	Audit process description
Loan Administration	**Collections & Loss Mitigation**
Usual approach to new loan origination and to loan reconciliation	A/R collection strategies
Bankruptcy & Enforcement	**Technology**
Bankruptcy related procedures	Level of digitisation and IT integration

E.4 Fitch Group. Criteria for Rating Granular Corporate Balance-Sheet Securitisations (SME and CLOs)

To derive a transaction's default probability expectation Fitch uses a top-down approach, first determining a default probability expectation for the SME market of the country. In the next step, Fitch determines how the originating bank SME loan book will perform in relation to the country, but does not tackle directly the credit risk of the SMEs.

E.5 Scope Credit Rating GmbH

The standard approach is top-down, that is, distributional assumption on the default rate of the SMEs are drawn from a probability distribution function, depending on macroeconomic factor. Anyway, if the SMEs exposure within the security is higher than the 2 percent of the total value of the security the company validates the statistically-predicted value with the proprietary corporate rating method. Still, out of 88 published corporate rating, only two (less than the 3 percent of the total) are rating of SMEs.

E.6 S&P Risk-Adjusted Capital Framework

The RACF is the methodology applied by Standard and Poor's to assess bank credit risk. Anything of relevant interest is mentioned for what concern specific SMEs credit risk assessment. As for Moody's approach, the two primary sources of information are bank own credit risk assessment. A generic statement from the S&P affirm that the rating agency might complement said information with additional information.[1] Whenever data on SMEs are not available, the risk of SME exposure is simply classified as a generic corporate exposure and is assigned a generic risk weight on the basis of generic distributional assumption drew from historical performance of similar sized asset.

[1] The source or the nature of said additional information is not clarified.

Appendix F

ECAIs: Methodologies for Corporate SMEs Rating

Description of European CRAs' methodologies for corporate SMEs' credit risk evaluation.

F.1 Axesor S.A.

Monitoriza One is the SME version of the risk management tool commercialised by Axesor. Nevertheless, no reference is made to a rating model specific for SMEs. No other documents are disclosed beside form a standard corporate rating approach.

F.2 CRIF S.p.A.

Despite claiming solution for SMEs, the company does not publish any explicit methodology for the category.

F.3 Euler Hermes Rating GmbH

The company, in partnership with Moody's is planning to enter the market of SMEs rating in the short term. The company will provide ratings to German enterprises. No detail regarding the methodology are provided yet.

Appendix G

Corporate Credit Risk in some major EU Banks

List of the major European banks by total assets, and related description of the corporate credit risk Corporate Credit Risk (CCR) in place for SMEs exposures. All the information have been taken from official corporate publications.

G.1 HSBC Holdings

Statistical model built on internal behavioural data and bureau information, and calibrated to a long-run default rate.

G.2 BNP Paribas

Logistic regression. PDs calibrated on internal long-run default data. Rule-based expert model.

G.3 Deutsche Bank

Ratings for SMEs combine quantitative analysis of financial information with qualitative assessments of industry trends, market position and management experience. Financial analysis has a specific focus on cash flow generation and the counterparty's capability to service its debts, also in comparison to peers. We supplement the analysis of financials by an internal forecast of the counterparty's financial profile where deemed to be necessary. Ratings for SMEs clients are based on automated sub-ratings for e.g. financial aspects and conduct of bank account. Credit Agricole Group The methods used cover all types of counterparty and combine quantitative and qualitative criteria.

G.4 Barclays PLC

- < EUR 20 million Statistical model that uses regression techniques to derive relationship between observed default experience and a set of behavioural variables

- > €20 million Statistically derived model sourced from an external vendor (Moody's riskcalc)

G.5 Société Générale

Statistical-type models (regression) for the rating process, based on the combination of financial ratios and a qualitative questionnaire.

G.6 Banco Santander

The PD is calculated by observing new defaults in the portfolio and relating these defaults to the ratings assigned to the customers concerned. Statistical models, based on internal default experience. adjusted to the economic cycle

G.7 Groupe BPCE

For these segments (companies, large corporates, banks, sovereigns and specialized financing), the rating system rests on two pillars. Quantitative and qualitative assessments of the counterparty's creditworthiness. When the Group does not have an internal model, it must estimate capital requirements based on corresponding parameters according to the conditions of the standardized approach. These are based in particular on the credit valuations (ratings) estimated by rating agencies recognized by the supervisor as meeting ECAI requirements, in particular Moody's, Standard & Poor's and Fitch Ratings.

G.8 Royal Bank Of Scotland

As part of the credit assessment process, RBS assigns each customer a credit grade reflecting its PD. RBS maintains and uses a number of credit grading models which consider risk characteristics relevant to the customer, incorporating both quantitative and qualitative inputs.

G.9 Lloyds Banking Group

In general the Group PD models are built using logistic regression. The PD models are all bottom-up style models, based on a number of counterparty-specific or account-specific factors.

G.10 UBS AG

UBS Limited uses three recognised ECAIs, S&P Moody's and Fitch

G.11 UniCredit S.p.A

ITA: EUR 5-250 million The structure of the rating system consists of three basic modules, two of which are quantitative and one qualitative:

- The economic-financial module, that considers the financial statements information in the archives of the Central Financial Statements Archive (Sistema Centrale Bilanci) (cash flow and profitability, financial charges, financial structure and composition of debt, financial stability and liquidity; growth, volatility and operational structure);

- the behavioural module, that, considering only the external source data obtained by both first sending streams and return ones of Central Credit Archive (Centrale Rischi), allows customers monitoring either toward the Group and the entire banking system (cash loans: withdrawal, short-term maturity, long-term maturity, self-liquidating loans; loan guarantees: commercial, financial; collateral);

- the qualitative module, that considers the answers to the questions of the qualitative questionnaire filled out during the application phase. Unlike in previous versions of the model, the qualitative component was developed with a total statistical approach.

DEU: EUR 5-500 million The model comprises a quantitative and a qualitative module. The score resulting from the analysis of financial statements is complemented by additional factors, resulting in a partial hard-fact rating. The qualitative model provides the partial rating for the company's situation. The final rating is created by combining the two partial ratings.

The quantitative module consist of four different financial statement sub-modules (MAJA - Maschinelle Analyse von Jahresabschlüssen) depending on the company's industry sector (Production, Trade, Construction, Services). Each of them combines a set of financial ratios that cover areas of analysis such as:

- asset and debt structure;

- cost structure, liquidity;

- profitability.

The automated assessment of the financial statement is complemented by additional factors regarding current company development, quality of financial statement and specifics of industry sector.

The qualitative module covers areas of analysis concerning:

- financial conditions;

- management qualification;

- planning and controlling;

- industry/market/products;

- special risk;

- industry sector rating.

Other SMEs The rating is assigned to these counterparts based on an external country specific quantitative component, which is integrated with an internally developed qualitative module leveraging on the correspondent module defined for German Mid Corporate segment.

Also for this model rating aging restriction rules are considered as well as possibilities of override. Due to an initial lack of data, it has been based on externally developed models from Moody's and complemented by internal qualitative components

G.12 ING Group

For SMEs, models are more regional or country specific. Models for SMEs companies, and larger corporates, institutions and banks are manually updated, and are individually monitored on at least an annual basis.

G.13 Credit Suisse Group

Mid-sized Statistical scorecards using e.g.retail balance sheet, profit & loss data and qualitative factors Small Merton type model using e.g. loan-to-value, collateral volatility and counterparty attributes

G.14 BBVA

Takes into account quantitative factors derived from economic and financial information, and qualitative factors that are related to the age of the company, the sector, management quality, etc. and alert factors derived from risk monitoring.

Appendix H

Scoring and alarm grid from a non-disclosed French bank

Table H.1: Example of scoring grid from of French bank

scores / *factors*	1	2	4	5
BoF score[1]	3++, 3+, 3	4+, 4, 0	5+, 5, 6	7, 8, 9
$\frac{\text{Shareholders' Equity}}{\text{Total asset}}$	$> 40\%$	$40\% - 20\%$	$20\% - 10\%$	$< 10\%$
$\frac{\text{Shareholders' Equity}}{\text{EBITDA}}$	< 3	$3 - 4$	$4 - 5$	> 5
$\frac{\text{Total Net Debt}}{\text{Shareholders' Equity}}$	%			
$\frac{\text{Interest Expenses}}{\text{EBITDA}}$	$< 30\%$	$30\% - 50\%$	$50\% - 60\%$	$> 60\%$
$\frac{\text{EBT}_t}{\text{EBT}_{t-1}}$	Amount			
$\frac{\text{Gross Profit}_t}{\text{Gross Profit}_{t-1}}$	$> 100\%$	100%	$> 95\% < 95\%$	
Managerial skills	Very good	Good	Average	Unknown
Industry trend	High growth	Growth	Sluggish	In crisis

Table H.2: Scoring grid — Details

Risk profiles	
7-14 pt.	No foreseeable difficulties. Partnership.
15-20 pt.	Current operating loans. No unsecured medium term loans.

[1] Bank of France

21-29 pt.	No increase in bank overdraft. No mid-term loan. Close monitoring
30-35 pt.	Refusal of any loan.
	Alarms
In case of an alarm	No increase in bank overdraft. No mid-term loan. Close monitoring
BoF Score	6 or 7 or 8 or 9
Undercapitalisation	$\frac{\text{Shareholders Equity}}{\text{Total Assets}} < 10\%$
Overindebtness	$\frac{\text{Total (net) Debt}}{\text{EBITDA}} > 5$ and $\frac{\text{Total (net) Debt}}{\text{Shareholders' Equity}} > 1$
Unprofitability	$\frac{\text{Interest Expense}}{\text{EBITDA}} > 60\%$ and/or $\frac{\text{EBT}_t}{\text{EBT}_{t-1}}$ in deficit

Appendix I

Scripts

Here following the R code for the neural network

```
>
> ####
> #
> # load library
> #
> ####
>
> library(tensorflow)
>
> ####
> #
> # Import data
> #
> ####
>
> companies <- read.csv("companies_large_norm.csv",header=T)
> companies <- companies[,c(1,2,8:19)]
> active <- companies[which(companies$Active == 1),]
> default <- companies[which(companies$Default == 1),]
>
> ### SAMPLE 5000 active and 5000 default for testing purposes
>
> smp_act <- sample(nrow(active), size = 5000)
> smp_def <- sample(nrow(default), size = 5000)
> test <- rbind(active[smp_act,],default[smp_def,])
> test <- test[sample(nrow(test)),]
> train <- rbind(active[-smp_act, ],default[-smp_def, ])
> train <- train[sample(nrow(train)),]
> train_active <- active[-smp_act,]
> train_default <- default[-smp_def,]
> test_values <- as.matrix(test[,3:ncol(test)])
> test_labels <- as.matrix(test[,1:2])
>
> #####
> #
> # build the mlayer perceptron
```

```
> #
> #####
>
> n_classes <- 2L
> n_nodes_l1 <- 50L
> n_nodes_l2 <- 25L
> keep_prob = 0.97
> x_length <- as.integer(ncol(companies)-2)
> ### Initialize weigths and biases with values
> from truncated std. normal
>
> weight_variable <- function(shape) {
+   initial <- tf$truncated_normal(shape, stddev = 0.1)
+   tf$Variable(initial)
+ }
> bias_variable <- function(shape) {
+   initial <- tf$constant(0.1, shape = shape)
+   tf$Variable(initial)
+ }
> ### define connections within the network
>
> x <- tf$placeholder(tf$float32, shape(NULL, x_length))
> hl1_W <- tf$Variable(tf$truncated_normal(shape(x_length, n_nodes_l1),
+
+
> hl1_b <- tf$Variable(tf$zeros(shape(n_nodes_l1)), name = "B_hl_1")
> hl2_W <- tf$Variable(tf$truncated_normal(shape(n_nodes_l1, n_nodes_l2),
+
+
> hl2_b <- tf$Variable(tf$zeros(shape(n_nodes_l2)), name = "B_hl_2")
> out_W <- tf$Variable(tf$truncated_normal(shape(n_nodes_l1, n_classes),
+
+
> out_b <- tf$Variable(tf$zeros(shape(n_classes)), name = "B_outupt_layer")
>
> ### define activation and droupout function
>
> l1 <- tf$add(tf$matmul(x,hl1_W),hl1_b)
> l1 <- tf$nn$relu(l1)
> drop1 <- tf$nn$dropout(l1, keep_prob)
> l2 <- tf$add(tf$matmul(drop1,hl2_W),hl2_b)
> l2 <- tf$nn$relu(l2)
> drop2 <- tf$nn$dropout(drop1, keep_prob)
> out <- tf$add(tf$matmul(l1,out_W),out_b)
> y <- tf$nn$softmax(out)
> ### placeholder for output variable
>
> y_ <- tf$placeholder(tf$float32, shape(NULL, n_classes))
>
> ### error function
>
> cross_entropy <- tf$reduce_mean(-tf$reduce_sum(y_ * tf$log(y),
```

```
+
>
> ### declaration of the backpropagation
> ### optimization algorithm (ADaptive Moment estimation)
>
> optimizer <- tf$train$AdamOptimizer()
> train_step <- optimizer$minimize(cross_entropy)
>
> ### store and reload partially trained model if needed
>
> # do not run first time
>
> #loader = tf$train$import_meta_graph("folder")
> #loader$restore(sess, tf$train$latest_checkpoint("folder"))
>
> #saver$restore(sess, "folder")
>
> ### do not run when loading
>
> init <- tf$global_variables_initializer()
> sess <- tf$Session()
> sess$run(init)
>
> ### Define accuracy metrics
>
> correct_prediction <- tf$equal(tf$argmax(y, 1L), tf$argmax(y_, 1L))
> accuracy <- tf$reduce_mean(tf$cast(correct_prediction, tf$float32))
>
> ### Define summary statistics to be monitor training
> ### (accuracy and and weigths)
>
> summary <- tf$summary$scalar("accuracy", accuracy)
> summary_CrossEntropy <- tf$summary$scalar("cross entropy",
+
> summary_hl1_W <- tf$summary$histogram("weights1",hl1_W)
> summary_hl2_W <- tf$summary$histogram("weights2",hl2_W)
> summary_output_layer_W <- tf$summary$histogram("weightsOut",out_W)
> summary_w <- c(summary_hl1_W,
+                summary_hl2_W,
+                summary_output_layer_W
+ )
> summary_weights <- tf$summary$merge(summary_w)
> log_writer <- tf$summary$FileWriter(paste0("folder",j))
> saver <- tf$train$Saver()
>
> ####
> #
> # Train the model
> #
> ####
>
>   for (i in 1:5000) {
```

```
+
+     ### random selection of the training batch
+
+     train <-  rbind(train_default,
+                     train_active[sample(nrow(train_default)),])
+
+     ### shuffle
+
+     train <- train[sample(nrow(train)),]
+
+     ### separate input (col 1 and 2) from labels (remaining columns)
+
+     train_values <-  as.matrix(train[,3:ncol(train)])
+     train_labels <-  as.matrix(train[,1:2])
+
+     batch_xs <- train_values
+     batch_ys <- train_labels
+
+     sess$run(train_step,
+              feed_dict = dict(x = batch_xs, y_ = batch_ys))
+
+     ### save accuracy on testing sample each 10 iteration
+
+     if(i %% 10 == 0){
+       accuracy = sess$run(summary,
+                    feed_dict = dict(x = test_values, y_ = test_labels))
+
+       log_writer$add_summary(accuracy, i)
+
+       error = sess$run(summary_CrossEntropy,
+                    feed_dict = dict(x = test_values, y_ = test_labels))
+       log_writer$add_summary(error, i)
+
+       weigths = sess$run(summary_weights)
+       log_writer$add_summary(c,global_step = i)
+     }
+
+     ### save entire model each 100 iterations
+
+     if(i %% 100 == 0){
+       saver$save(sess, "folder", global_step=i)
+
+     }
+   }
>
> ####
> #
> # Show stats
> #
> ####
>
> ### print confusion matrix, balanced accuracy and accuracy
```

```
>
> prediction = tf$equal(tf$argmax(y, 1L), 2L)
> pred = sess$run(tf$argmin(y, 1L), feed_dict=dict(x = test_values,
+
> conf.mat <- table(Predictions=pred, Actual=test_labels[,1])
> conf.mat
>
> bal.accuracy <- (conf.mat[1,1]/sum(conf.mat[,1]) +
+                                 conf.mat[2,2]/sum(conf.mat[,2]))/2
> bal.accuracy
>
> sess$run(accuracy, feed_dict=dict(x = test_values, y_ = test_labels))
>
>
```