Scuola di Ingegneria Industriale e dell'Informazione
Corso di Laurea Magistrale in Management Engineering

Creditworthiness:
A supply-chain oriented perspective

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Master Thesis

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Academic year: 2016/2017

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ABSTRACT

The tough economic scenario and the recent financial crisis has dramatically affected how companies can access to credit. The exposure to risk faced by financial institutions has increased, causing the so-called *credit crunch*, a situation in which the supply of credit dramatically decreases and where banks do not trust debt issuers increasing the average cost of debt. In this complex scenario, banks are always struggling to improve creditworthiness assessment models. In literature, the primary role of financial information as source for the credit rating determination is undisputed. However, the so-called *soft-factors*, like supply-chain operative performances, are not currently considered in the process. Following the Supply Chain Finance approach, the present work exploits a wide range of methodologies (from statistical analysis to focus group) with the aim of formulating and validating an innovative credit rating framework that includes vendor rating data.

ABSTRACT

La difficile scena economica attuale, la recente crisi finanziaria e la recessione hanno impattato negativamente la disponibilità di accesso al credito da parte delle aziende. Parallelamente, il rischio di credito percepito dagli enti finanziatori, quali banche e istituti di credito, è stato amplificato provocando quella che viene chiamata trappola del credito o *credit crunch*. In questo scenario, le banche sono sempre alla ricerca di modelli più efficaci ed affidabili che predicano il default di impresa. In letteratura, è largamente riconosciuto il ruolo dei dati finanziari come fonte principale nella definizione del rating di impresa. Tuttavia, aspetti più "*soft*", come le performance operative, non sono attualmente considerate nella valutazione del merito creditizio. Attraverso varie metodologie (da analisi statistiche empiriche a focus group), il presente lavoro arriva a formulare e validare una framework concettuale per la valutazione del merito creditizio che incorpori anche dati di vendor rating dei fornitori.

EXECUTIVE SUMMARY

Introduction

The *credit crunch* and the strict regulations imposed to banks have caused a sharp decline in bank credit supply. Still the economic downturn of recent years has pushed down firms' profits to hit historic lows.

In addition, the complexity and the uncertainty are growing worldwide even in the most stable industries. In such an unpredictable environment, companies are struggling to access the credit because banks perceive a higher exposure to risk and, so, have become more risk adverse. Consequently, credit is "trapped" and the cost of debt (margin of banks as a remuneration of risk faced) has raised dramatically. The more banks increase their credit supply, the more they are exposed to risk. Thus, banks are always looking for improvements in the way the creditworthiness of a company is assessed. A better understanding of the creditworthiness of debt issuers lead to a reduction in their risk exposure and, consequently, to an increase of the credit supply in the market.

Thus, more and more academics, financial institutions and firms are working together in order to find alternative sources of funding to mitigate the risk of another financial crisis. Supply Chain Finance is a fast-growing and cross-disciplines field of study that aims at optimizing financial flows in supply-chains via innovative techniques of funding. Given this wideness, several independent streams exist within SCF framework. One of them supports the view that sharing data about vendors' operative performances with external stakeholders (e.g. banks and financial institution) would provide several benefits to the whole supply-chain.

To reach the goal of improving the accuracy of credit rating models, academic literature has always focused on developing more and more advanced statistical techniques. Recently, different perspectives have arisen. Fernandes et al (2015) claim that investments in information, rather than techniques, can lead to higher gain in predictive performances. In other words, introducing new sources of data within existing credit rating models pays back more than refining existing modeling techniques.

The present work stems from this last perspective as the objective is the development of a supply-chain oriented creditworthiness framework. The importance of this work lies in its cutting-edge nature. In fact, the approach is *theory-building* as there is no proof of previous researches on this subject.

Literature review

The first step of the present research has been an accurate analysis of existing academic literature. This helped to understand the current development status of the research in this field and to spot valuable research opportunities to pursue. This analysis followed three different perspectives: *financial*, *vendor rating* and *supply-chain finance*.

The Financial Perspective

The first perspective that has been analyzed is the financial one. The notion of creditworthiness has found great interest in academic since the '30s and it represents the most mature field of our literature review.

Creditworthiness can be defined as "*a presumed ability to meet agreed deadlines related to repaying the credit and the interest accrued without affecting the vitality of the borrower, i.e. the repayment process should be based on the income received in the process of the borrower's usual activity, without affecting adversely his financial situation, his financial results as well as other business entities*" (Feschijan, 2008).

The notion of creditworthiness is strictly connected with the concept of *Credit Risk*, which is defined as the probability that one of the two counterparts of a contract does not meet its obligations and create a loss for the borrower (Ammann, 2001). Dozens of researchers have tried to find innovative solutions to effectively predict companies' default. One of the reasons behind the great interest towards this theme is the high value that an accurate predictive model has for banks and financial institutions. Institutions have always been aware of the importance of regulating the way creditworthiness is assessed and, through the history, some rules have been developed.

The Basel accords– Basel I, Basel II and Basel III – are a set of banking regulations in the banking industry set by the Basel Committee on Bank Supervision (BCBS). The aim of these accords is to ensure that financial institutions have enough capital on account to meet obligations and absorb unexpected losses.

In Basel II the key concept of Credit Rating has been defined as *"the set of the methods, processes, controls, data and information systems that support the assessment of credit risk, the assignment of internal worthiness degrees and to the quantitative estimation of defaults and losses"*. The assessment of the credit risk is mainly based on the analysis of the financial risk, but also a wide range of factors are considered, even if with a lower weight. In fact, factors, as industry risks, business risks and management skills, can have an impact on the debtholder ability to repay its obligations. However, even if credit scoring models are widely explained in literature, the determination of credit rating is still not clear. Many researchers argue that financial information account for most of the weight in credit rating but there is lack of empirical proof of this. Each bank or credit rating agency tend to vary only in their weighting of the individual parts of the credit analysis.

Due to the 2007 financial crisis, the number of defaulted companies has increased worldwide. Thus, it is increasingly important to identify accurate frameworks to evaluate the creditworthiness of a third part. A reliable credit rating model corresponds to a more precise prediction of the default probability of a company. Thus, better models can create value for both banks and lending institutions. In this research only statistical credit model models will be discussed.

Since the beginning of the 20th century, a lot of studies regarding the balance sheet have been made with the objective of measuring the economic and the financial performances of companies. However, even if the balance sheet itself provides relevant information to assess a company's financial position at a certain point of time, it is not enough to forecast future economic and financial performances of the company. Information on balance sheet needs some degree of elaboration before they can have a predictive power. If used alone, the balance sheet is not able to describe the complexity of the business situations. To overcome this limit, scholars focused on performing statistical analysis to assess companies' creditworthiness.

The output of this kind of analysis are called *Credit Scoring* models. They involve the combination of quantitative (e.g. financial ratios) and qualitative information (e.g. payment history) to assess the company's creditworthiness. In this research, only the most acknowledged credit scoring model in the academic sphere have been deeply analyzed: Z-Score (Altman, 1968), Z'-Score (Altman, 1993), Z"-Score (Altman, Hartzell and Peck, 1995), O-Score (Ohlson,

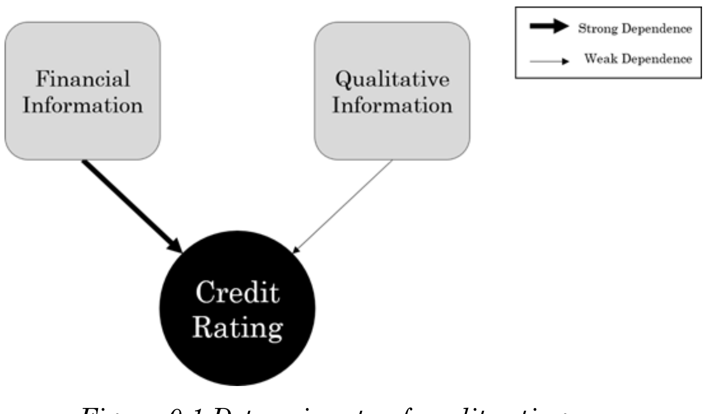

Figure 0.1 Determinants of credit rating

1980) and Zmijewski (1984). It is interesting to notice how credit scoring models have adapted to changes of the external environment.

For instance, as external stakeholders' awareness about sustainability issues is growing rapidly, sustainability-oriented metrics are appearing in predictive models. Furthermore, even if many models have been developed to include innovative variables, vendor rating data have never been taken into consideration.

Vendor rating can be considered part of the so-called *weak-signals*, all those information that are characterized by a certain ambiguity but they can have an anticipatory predictive power if interpreted correctly. The adjective *weak* means that they have no ambition to replace financial information as major predictors, but they can integrate the assessment providing a more complete picture.

Vendor rating

Nowadays, supply chain risk has become one of the major issue for companies. Furthermore, the recent financial crisis and the subsequent uncertain economic stability posed great attention on identification and mitigation of supply risk within companies. Supply networks have become more and more strategic while they broaden their boundaries becoming global. Among many different risk sources, academic literature considers supplier's default risk as potentially disruptive for both buyers downstream and suppliers upstream. In fact, the supplier's default has two major consequences on supply-chains equilibrium. First, the *domino* effect caused by the contagious effect of failure. Zhou (2001) define the existence of correlation when "*the likelihood of one company's default is affected by the default of other companies*". Second, buyers adopt more and more multi-source strategy to mitigate the risk of supplier's potential default. The supply-base widens and buyers must bear higher costs to mitigate the risk.

In such a context, the supplier evaluation and selection process has become more and more critical as the choice of the right supplier can make the difference between winning and losing the competition. This process is very complex and involves several different actors. This works focuses on the part of the process that takes place after a supplier is engaged: monitoring active suppliers' operative performances through a structured set of metrics that are frequently updated. The set of scores that are assigned to suppliers are called *vendor rating*.

Vendor rating is a process that evaluate operative performance of existing suppliers to monitor and drive the relationship over time. Each company designs the set of KPIs that wants to take under control, according to its own strategic vision. Due to its high relevance, vendor rating has been object of uncountable academic researches.

Academic literature has always focused on understanding what are the most important attributes on which evaluate a supplier. From the earliest works (Dickson 1966) to the latest (Gunasekaran 2001), researchers have dealt with the trade-off between completeness of information keeping the number of metrics at the minimum. Particular attention has been posed in the identification of the most important vendor rating criteria to be used to evaluate a supplier.

As far as vendor rating is concerned, the literature review demonstrated that data are characterized by a *high diversity and customization* because they are collected at the physical level of supply chain. First, each competitive arena has its own *critical success factor* and this lead to different metrics for vendor rating. Furthermore, here is where companies take decision to differentiate from the competitors. Thus, even in the same marketplace, companies that pursue different strategies will evaluate suppliers accordingly. This inherent heterogeneity makes the vendor rating data *incomparable* and *unstandardized*. A second major research gap about vendor rating data is a *lack of empirical analysis that investigate their predictive value*. Some researchers have started claiming the importance that operative performances can have in predicting companies' future. However, these considerations lie at a theoretical level. In other words, there is not empirical study that tries to integrate vendor rating as information to help evaluating creditworthiness.

Supply Chain Finance

The last topic that has been analyzed in the literature review is *Supply Chain Finance*. SCF is an innovative field of study that focuses on solutions that can help to improve financial flows throughout the supply-chain. The key-values that drive SCF solutions are *transparency* across the whole supply chain and *collaboration* between actors to achieve win-win situations. SCF is based on collaboration between stakeholders and visibility across the whole supply-chain.

Given the heterogeneous nature and the lack of history, many different frameworks are spreading. For the purpose of this research, the key trait from SCF is the collaboration between buyers, suppliers and financial institutions. In fact, one of the cornerstone of SCF is a strict collaboration between actors to ensure the stability of supply-chain and favor the flow of financial resources throughout the supply-chain.

Two key-concepts to understand Supply Chain Finance principles, are the *Working Capital* and the *Cash-to-Cash* cycle. These two metrics provide indication about the financial management of the supply-chain. Supply chain manager must always keep under control these KPIs since they are critical for the stability of the whole Supply Chain.

For the purpose of this work, SCF principles has acted as a reference for the development of the analysis. In fact, transparency and collaboration between stakeholders, have been guidelines that supported the designing of the study and the formulation of the solution.

Here, the main research gap that has been identified is a *lack of common and structured framework*. This results in several independent perspectives that slightly differ between each other. Finally, there are still empirical researches that confirm benefits of the integration of the financial and physical flow.

From Gaps to Questions

In the following table, there is a recap of the main research gaps that have been identified in literature review for each of the theme discussed in the literature review.

RESEARCH GAPS		
Credit Rating	**Vendor Rating**	**Supply Chain Finance**
Lack of transparency in the credit worthiness assessment process	Poor homogeneity and comparability	Lack of a common structured framework
Lack of supply-chain perspective in assessing credit worthiness	Lack of empirical analysis of predictive value of vendor rating	Few empirical analysis of integrated approach

Table 0.1 Summary of research gaps found in literature review

Research gaps are then translated into formal and structured research questions and addressed with specific research methodologies.

RQ0: Understanding determinants of credit rating

The first issue, that the present research wants to address, is about the problem of the *lack of transparency in credit rating determinants*. From the literature review, it results that there is low transparency about the entire process of credit rating assessment done both by financial institution and external rating agencies.

From the literature review, we know that credit rating is determined starting from two main set of information, which contribute to the definition of the final result. These two fundamentals “bricks” are *financial data* and *qualitative data*. There is wide acceptance in literature that financial data account for most of the overall credit rating and they have the largest weight in the determination of the final result. Given that the goal of this thesis is the creation of a supply chain-oriented creditworthiness framework, this first research question aims to provide some insights about the determinants of credit ratings in the current scenario.

Therefore, the first research question could be formulated as follows:

RQ0: *"Are credit scoring models consistent with credit rating ones? How much is the credit scoring's weight in the determination of the final credit rating?"*

RQ1: Evaluating the potential of Vendor rating data

The second research question introduces the innovative component of the research: *vendor rating* data. This research question represents a preparatory step for the actual integration of vendor rating data in the process of credit rating assessment.

The goal is to verify whether the information included in vendor rating data are already "explained" by inside variable like financial data or credit rating. The reason why this research question has been included in the study is that, every time there is the possibility of introducing new variables into a model, several considerations about the incremental gain of model performance must be done.

In other words, it must be discussed whether the introduction of a new source of data in a credit rating model would bring additional information or not. If the addition of this kind of information resulted redundant, it would mean that almost all the informative potential is already explained by some other variables already present in the model. In fact, although vendor rating data and financial information are two independent concepts, with different measures and actors involved, it could be that financial data variability already reflect vendor rating one, making the introduction of the latter, unnecessary.

Therefore, the second research question is formulated as follows:

RQ1: *"Would vendor rating data be redundant in a creditworthiness assessment model?"*

RQ2: Integrated supply-chain oriented creditworthiness framework

In the first and the second RQs, the focus was on having an understanding about how the credit rating is built (RQ0) and whether vendor rating data could represent a missing piece of information in credit scoring models (RQ1). The third research question represents the last step of our work and it aims to provide an innovative contribution to the existing literature on this field.

The first goal is to identify how vendor rating information can be structured and aggregated in order to be used inside credit rating models. There is the need to design a way to elaborate vendor-rating data with the objective of improving their usability and facilitating their integration inside existing credit rating models. As already pointed out in the literature review, vendor rating data that come from different buyers are scarcely comparable because of differences that exist between industries and companies' strategy. Since this heterogeneity is driven by the need to adapt to the market environment, the goal is to develop a model that could cope with those differences.

The second goal of this research question is about validating the integration of vendor rating data in creditworthiness models. It consists in demonstrating that a supply-chain oriented creditworthiness framework would be beneficial for the overall systems.

Finally, the work is concluded with the development of an innovative credit rating framework that includes, also, this new source of information to assess companies' creditworthiness.

Therefore, the third hypothesis could be formulated as follows.

RQ2: *"Is it possible to develop a "supplier rating"? Would the introduction of vendor rating data improve creditworthiness models?"*

Research methodology

Once the research gaps have been identified and they have been translated into punctual research questions, the final step of the design phase is represented by the choice of *research methodologies*.

Given the complexity of the research, a single methodology would have been too restrictive. Thus, three different methodologies have been chosen.

In the following table, a summary of all the methodologies is presented.

Research methodology	Description	Research question
Literature review	Identification of research gaps	Formulation of RQs
Statistical models	Correlation matrixes ANOVA Student's t-tests	RQ0/RQ1
Focus Group	Three-rounds workshop with experts	RQ2

Table 0.2 Summary of research methodologies, descriptions and related RQs

Literature review

First, a review of existing academic literature (papers, research journals and books) helped us to understand the state-of-art of the research, in order to identify latest trends and to spot research gaps to address. Practically, the methodology has followed three different perspectives: *financial*, *vendor rating* and *supply-chain finance*. For each topic, great effort has been put in place in order to collect and analyze several sources of information. As already discussed, literature review is a fundamental methodology in every research work, as it is the starting point to define the following steps. Thus, the main contribution of literature review is the translation of research gaps into research questions.

Statistical models

Once research questions have been formulated, data collection process has started. In particular, three kind of data has been collected: vendor rating data, credit rating data, financial information.

Samples have been exported independently from three different sources (*AIDA*, *Niuma* and *BPER Banca*) and then matched to obtain samples compliant with each research question's objectives. However, the reader can have a better understanding of the data collection process in Paragraph 4.1.

This second category of research methodologies, called *statistical models*, include different tools such as *correlation matrixes*, *ANOVA* and *Student's t-tests*. Furthermore, visual tools like *scatterplot graphs* have been used to support the interpretation of results.

These statistical tools have been used to investigate correlations and differences between variables and, so, to support the discussion on RQ0 and RQ1. The choice of statistical models has been done to provide robustness to the results of the research. In fact, if structured correctly, the statistical approach is more rigorous and its conclusions are more valuable since they are characterized by a high degree of objectivity.

As far as RQ0 is concerned, the focus is investigating the relative importance of financial data in the determination of the credit rating. For this purpose, only two variables have been considered: credit scores and credit rating. However, since there are several credit scoring frameworks in literature, we decided to include the most acknowledge five and to analyze their correlation against the credit rating. In order to analyze the correlation between these two dimensions, a *non-parametric correlation matrix* and *ANOVA* has been exploited.

Regarding RQ1, the scope is understanding whether the informative power of vendor rating data would be worth the effort of integrating them inside creditworthiness assessment models or not. Statistically speaking, this objective is translated in testing how much vendor rating data are correlated with both credit scoring and credit rating. In this case, *non-parametric correlation matrix* and *Student's t-test* have been used to respond to the research question.

The reader can fin more details about statistical methodologies in Paragraph 4.2.3.

In order to support the statistical analysis of RQ1, some scatterplot graphs have been created to provide a different perspective of the problem. In fact, thanks to a visual representation of data, a practical characterization of real scenarios is possible. The rationale behind the choice of including visual tools in the analysis is linked to the fact that they are able to provide a different perspective of the same problem.

Focus group

The focus group is the unique methodology that has been used to answer to RQ2: the development of the innovative supply-chain oriented creditworthiness framework. The focus group has been chosen among many possible methodologies thanks to its wide adoption in literature and thanks to its good fit with *theory-building* studies.

In fact, it is characterized by an unstructured approach that favor interaction between participants and flexibility. Here, a group of experts from companies, banks and institutions gathered to discuss interactively about a topic. The discussion flows without rules, to encourage creativity and innovativeness.

Practically, this focus group has been performed in the form of a workshop structured in three meetings. The organization of the focus group has been possible thanks to the collaborations that the *SCF Observatory of Politecnico di Milano* has in place with many external actors. The complete list of participants is reported in Chapter 4.2.3.

In each meeting, all the participants joined an interactive debate about the agenda of the day. Directors and coordinators of the *Osservatorio SCF* acted as moderators in the discussion.

The overall objective of the workshop is discussing about the synthesis of these two apparently opposite worlds: vendor rating and creditworthiness. The group of participants have actively discussed about goals, benefits and challenges that must be considered in the integration of vendor rating data in credit rating.

The focus group was broken into three meetings:

- First meeting (14/07/16): *Environment analysis and problem recognition*
- Second meeting (12/10/16): *Problem setting and requirements analysis*
- Third meeting (14/12/16): *Design of the solution*

Discussion and results

RQ0: Understanding determinants of credit ratings

The first statistical analysis aims to better understand the relationship between two key dimensions in the model: credit scoring and credit rating. The rationale behind this analysis is the desire to throw light on the determinants of credit rating. From literature, it is acknowledged that credit scoring plays the major role in the determination of the final rating but empirical analysis that support this thesis are not common.

Thus, a *Spearman's correlation matrix* has been developed. The result is reported in table 0.4. It is clearly visible that the credit rating ("BPER Rating" on the left) is highly correlated with all the selected credit scoring models included in the analysis. (Altman Z' Score, Altman Z' Score, Altman Z" Score, Ohlson O-Score, Zmijewski model).

The missing part of the variance is explained by the fact that in the determination of credit rating there are also qualitative input that are outside the scope of this question.

The sign of the correlation coefficient is consistent for every credit scoring models. In fact, as the BPER BANCA rating decreases: on one side the Z-Score, the Z'-Score and the Z"-Score increase (negative correlation), and, on the other one, the O-Score and the Zmijewki score decrease (positive correlation). In particular, we can see that there is a strong negative correlation between the Altman's Z" Score and the BPER Banca rating.

The value of the correlation coefficient is high enough (-0.605) to show that there is a strong correlation between credit scoring and credit rating and, thus, we can state that financial information play a relevant role in the determination of credit rating.

The second statistical methodology that has been applied for the first RQ is the *One-Way ANOVA*. The objective on this analysis is to determine whether credit rating is significantly different in each of the groups identified by the Z"-Score of Altman: "Safe", "Grey Zone" and "Fail". The procedure followed these two steps.

First, all the companies in the sample has been grouped in different clusters according to the perceived

		BPER Rating	Z Score	Z' Score	Z" Score	Zmijewski Score	O Score
BPER Rating	Correlation Coefficent	1	-0,545	-0,496	**-0,605**	-0,437	0,392
	Sign.		0	0	**0**	0	0
	N	804	804	804	**804**	804	804

Table 0.3 Spearman non-parametric correlation coefficients

risk-level suggested by Altman's Z" model (*Safe*, *Grey zone* and *Fail*).

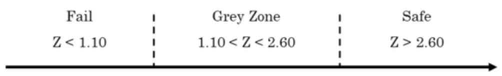

Figure 0.2 Risk-level clusters suggested by Altman's Z" Score model

Then, for each cluster the value of average BPER Banca credit rating has been compared with others.

First, from descriptive statistics it is possible to see that mean value (*Mean*) of credit rating decreases as the risk level decreases (Safe has better rating than Fail). This is the expected behavior.

From ANOVA results, the outcome is the level of statistical significance of the test (*Sign.*). Such a low *p-value* provides robustness to the analysis and allow to extend our consideration to the overall population.

In the end, the application of the Tukey's post-hoc test shows that all the differences between clusters are consistent with expected behavior.

This research question aimed at providing insights about how financial institutions determine the credit rating in the AS-IS scenario. Furthermore, the understanding of determinants of credit rating was a crucial step towards one of the goal of this research: the creation of a supply chain-oriented creditworthiness model.

Descriptive statistics

					95% Confidence Interval for Mean			
	N	Mean	Std. Deviation	Std. Error	Lower Bound	Upper Bound	Minimum	Maximum
Fail	267	4,98	1,73	0,11	4,77	5,19	1,08	9
Grey Zone	262	3,73	1,64	0,1	3,53	3,93	1	7,83
Safe	253	2,27	1,3	0,08	2,11	2,43	1	6
Total	**782**	**3,69**	**1,92**	**0,07**	**3,55**	**3,82**	**1,00**	**9,00**

ANOVA results

	Sum of squares	df	Mean square	F	Sign.
Between Groups	959	2	479	194	0,00
Within Groups	1927	779	2		
Total	**2885**	**781**			

Tuckey Post-hoc test results

					95% Confidence Interval for Mean	
(I) Z"-Cluster	(J) Z"-Cluster	Mean Difference (I-J)	Std. Error	Sign.	Lower Bound	Upper bound
Fail	**Grey Zone**	1,25	0,137	0,00	0,93	1,57
	Safe	2,72	0,138	0,00	2,39	3,04
Grey Zone	**Fail**	-1,25	0,137	0,00	-1,57	-0,93
	Safe	1,47	0,139	0,00	1,14	1,79
Safe	**Fail**	-2,72	0,138	0,00	-3,04	-2,39
	Grey Zone	-1,47	0,139	0,00	-1,79	-1,14

Table 0.4 SPSS output tables of ANOVA

RQ1: Evaluating the potential of Vendor rating data

The second step of this research introduces the dimension of vendor rating that is currently missing in credit rating models.

In particular, the objective is to understand whether the introduction of vendor rating data would bring additional information to the model or it is just a redundant dimension. In fact, it is possible that the variability of operative performance (measured by vendor rating data) is already "explained" by credit scoring or credit rating variation. In addition, statistical methodologies have been applied and this have enhanced the significance of the analysis.

This analysis has been supported by a visual representation of data obtained with scatterplot graphs. In these graphs, vendor rating data are compared, on the left, with credit scoring models and, on the right, with the BPER Banca credit rating.

These scatterplots provide several valuable insights. In fact, by splitting both dimensions with a cut-off equal to the mean value, four scenarios are defined. In two of them (2 and 4), vendor rating is consistent with the other dimension (High-High or Low-Low) while in the other two quadrants (1 and 3) they provide opposite visions (High-Low or High-Low)

In the chart on the left, scenarios with concordant dimensions account for the 46.32% of the total cases. This means that, in more than 50% of the cases, vendor rating can provide a meaningful perspective that could change the final rating. On the contrary, the information coming from vendor rating score and the other dimensions are consistent in less than the 50% of the cases. This is a first proof of the fact that there is the need of looking at both of the scorings to better depict the creditworthiness of a company.

The second statistical methodology that has been used in this RQ is the *Independent samples*

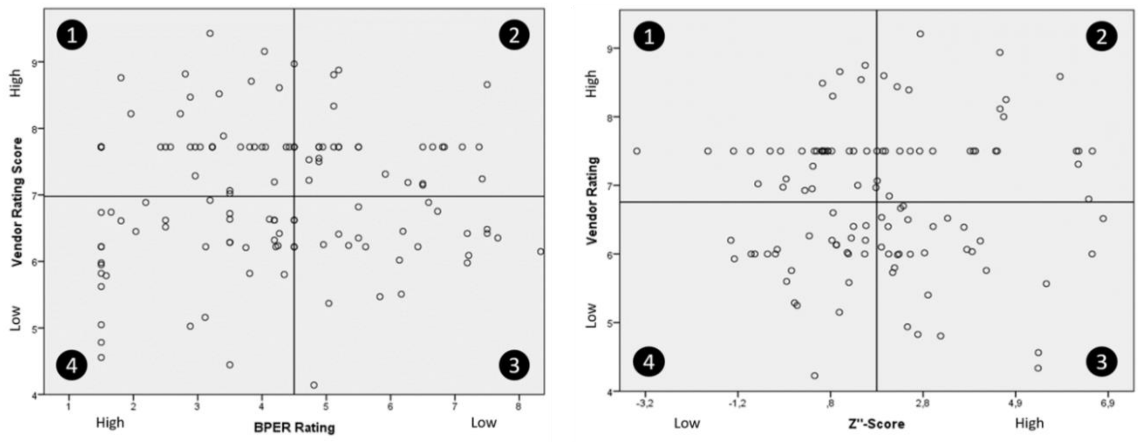

Figure 0.3 Matrixes that represent correlation between vendor rating (y-axis) with credit rating and credit scoring (x-axis)

Student's t-test. The objective is to understand whether vendor rating significantly differ between high-risk and low-risk companies classified according to Altman's Z" Score guidelines. Altman suggests that companies with a Z"-Score value greater than 1.85 are considered at low risk, on the other hand if that value is lower than 1.85 the companies have a high risk of default. The results of the test are reported in the table above.

From the descriptive statistics, it is visible that there is almost no difference of the vendor rating mean value between the two clusters. Furthermore, the high p-value of the t-Test (0,8) is a confirmation that a significant difference does not exist as far as is that there is not a statistically significant difference in mean of the vendor rating score between low-risk and high-risk companies. This confirm the fact that credit scoring (Z" Score) does not explain the variance of vendor rating.

The same test has been performed splitting the sample according to risk-levels suggested by BPER Banca rating. In particular, companies with credit rating lower than 4 are considered "safe". Afterwards, the mean value of vendor rating data has been compared between the two groups. Results are identical to the previous analysis: also credit rating data is able to explain the variability of vendor rating.

All the methodologies that have been applied confirmed that there is no sign of correlation between vendor rating data and any other variables that is already included in the model. No correlation between vendor rating data and credit scoring data means that financial information cannot explain the variation of operative performance by themselves. Furthermore, the absence of correlation between vendor rating data and credit rating suggests that operative performances are not taken into account neither in the "qualitative information" that differentiate credit scoring from credit rating.

Descriptive statistics

	Z"-Score Cluster	N	Mean	Std. Deviation	Std. Mean Error
Vendor Rating Score	**High Risk**	64	6,83	0,94	0,117
	Low Risk	70	6,79	1,11	0,132

Student's T-Test results

		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval for Mean	
							Lower	Upper
Vendor Rating Score	**Equal variances assumed**	0,24	132,0	0,810	0,043	0,178	-0,310	0,395
	Equal variances not assumed	0,24	132,3	0,808	0,043	0,177	-0,307	0,393

Table 0.5 SPSS output tables of Student's t-test

Thus, this research question represents a big step forward to the final goal of this research. The informative content of vendor rating data is a potential that it is "hidden" and it is still not exploited yet by any other informative source in traditional creditworthiness models.

RQ2: Integrated supply-chain oriented creditworthiness framework

This research question represents the last step of the research and the ultimate objective is to develop an innovative supply-chain oriented creditworthiness framework. This framework should combine the information coming from vendor rating systems with the financial ones with the scope of improving the way credit risk is evaluated.

Our work aims to provide a contribution to the literature review in this field. In fact, there is no evidence of existing studies that tried to build a creditworthiness rating model with vendor rating variables.

For this purpose, a theory-building methodology has been used: the *focus group*. The choice was driven by the good fitting that this technique has with the requirements of the RQ. The methodology followed a multi-step focus group articulated into three meetings, each one with a specific objective. Participants to the meetings were experts and managers coming from enterprises, banks and public institutions.

<u>First meeting: Environment analysis and problem recognition</u>

In the first meeting, the focus was on understanding the environment where supply chain finance operates and recognizing the need of taking into account vendor rating information when assessing the credit risk of a company. In RQ1, four different scenarios have been defined according to the values that vendor rating and traditional rating can assume. These scenarios have been discussed in the focus group and are represented in the following chart.

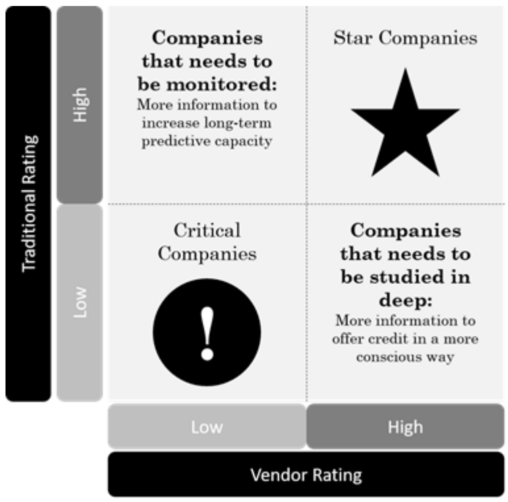

Figure 0.4 Matrix representing four scenarios identified by focus group

The previous chart identified two easily explicable situations: the ones for which the two dimensions are concordant. In one case, companies have a high performance in the traditional ratings model, but poor ones in terms of vendor rating. It is important to monitor this kind of companies, because vendor rating performances give information about the real-time trend. Thus, if they are poor, in the future even financial performances will decrease. This kind of companies are perceived as "safe" by the financial institutions, but, as we have just shown, a deeper investigation about the vendor rating dimension should be done in order to have a clearer view of the creditworthiness of these companies.

In the other case, we find the opposite situation. Just like the previous scenario, the focus group highlighted that there is the need to study in deep this kind of companies. In fact, despite of their poor financial situation, their vendor rating performances are more than satisfactory. Their credit risk is usually considered as "risky", but, in some cases, they may be safer than the companies previously analyzed.

<u>Second meeting: Problem setting and requirements analysis</u>

In the second meeting, the focus group addressed the problem of creating an intuitive, aggregated and qualitative supplier rating. Firstly, the focus group decided to focus on how vendor rating information should be assembled with the scope of developing a, so called, *Supplier Rating*. Since in the normal scenario a supplier has more than one client, also the ratings will be more than one for each supplier. Thus, here arise the problem of defining what affect the weight of a vendor rating evaluation.

In this meeting, the discussion focused on understanding all the factors that can affect the weight that a single evaluation has on the overall *supplier rating*:

- Strategic importance of the supplier for the customer, categorized in *strategic*, *important*, *minor*, in *test phase*. The more strategic a supplier is, the more weight the evaluation has.
- Weight of the supply on total revenues of the supplier, valued as *> 50%*, *25 – 50%*, *10 – 25%* and *<10%*. The bigger the portion of revenue, the more important the evaluations of the buyer.
- Duration of the relationship, classified as *< 6 months*, *6months – 2 years*, *2 – 5 years* and *> 5 years*. The longer the relationship, the more weight the evaluation has.
- Periodicity of the vendor rating evaluation. Recent evaluation are associated with larger weights Evaluation should be provided *weekly*, *monthly*, *quarterly* or *biannually*.

<u>Third meeting: Design of the solution</u>

In this last meeting, the main goal was to develop a synthetic formula that can be used to evaluate the *Supplier Rating* of a supplier. Starting from the output of the previous meeting, the focus group produced also a formula for the calculation of the weight that each evaluation has on the final supplier rating. In the final evaluation of a supplier, a greater weight is associated at the judgments provided by customers for which the supplier is strategic and their relationship is long lasting. The formula of the Supplier Rating highlights the importance that the customer weight must have in the definition of the supplier rating.

The final *supplier rating* is calculated according to the formula above. The second part of the *Supplier Rating* formula is the *Customer Evaluation*.

Here, the focus group agreed on the dimensions of vendor rating that have to be taken into account when looking at the operative performances of a company. The attributes have been kept as much general as possible because they refer to general concept that horizontal to every industry. In detail, the dimensions that take part of the *customer* evaluation are:

- *Quality of the Product*
- *Punctuality*
- *Pricing Factors,*
- *Flexibility,*
- *Relationship and skills management.*

As it visible from the formula of the Customer Evaluation, the same weight has been assigned to each dimension. The rationale behind this choice is the choice to keep the framework as much general as possible. In fact, since each industry and each buyer can assign different priorities to vendor rating performances, the only way to create a universal framework is to have a "democratic" approach assigning the same weight to each performance.

$$Supplier\ Rating = \frac{\sum_{i=1}^{n}(Customer\ Evaluation_i \times\ Customer\ Weight_i)}{\sum_{i=1}^{n} Customer\ Weight_i}$$

$$Customer\ Weight_i = \frac{(Strategic\ Weight_i + Relationship\ Duration\ Weight_i)}{2}$$

$$Customer\ Evaluation_i = \frac{(Quality_i +\ Punctuality_i +\ Pricing\ Factors_i +\ Flexibility_i +\ Relationship_i)}{5}$$

Figure 0.5 Formulas that build the *supplier rating*

“Supplier Advisor”: technical concept

The focus group introduced also the topic of *how* the *supplier rating* could be practically integrated inside existing process.

A rough concept based on the “*trip advisor*” platform has been introduced. Basically, this solution consists in the creation of an open platform in which each supplier is publicly evaluated by its buyers and data can be accessible by financial institutions as additional input for their creditworthiness assessment process. The focus group agreed that this platform should be managed by an external information provider, that act as a middle-agent and centralize all vendor rating data, elaborate them and make them accessible for other stakeholders. More details about benefits and challenges of this concept can be found in Paragraph 7.2.

Benefits

Banks could benefit by improving the creditworthiness assessment process and, thus, reducing their exposure to risk due to lower credit deterioration. Suppliers can benefit thanks to an easier access to credit due to a more reliable assessment from banks. In particular, for all those suppliers that currently present an unclear situation between financial and operative rating, this second perspective can provide a good chance to get credit at a more sustainable cost of debt. Finally, buyers could benefits, indirectly, of the easier access to funds of their suppliers.

Challenges

This solution has also some challenges.

- *Regulation*: particular attention must be brought in the compliance with Basel requirements. Since banks should make a change on how they currently assign ratings, a careful analysis of potential regulation obstacles should be performed.
- *Incentives to buyers*: since buyers are the real owners of vendor rating data, they must be incentivized in sharing them outside. In fact, such shared platform increased their value exponentially as the number of members increases.

Beyond traditional Creditworthiness models

A final contribution of this research is the concept of supply chain oriented creditworthiness framework. It represents a personal elaboration of the authors and all the following considerations are the results of the previous analysis performed in this research. A combination of literature analysis, statistical models and focus groups has led to the creation of the following conceptual framework.

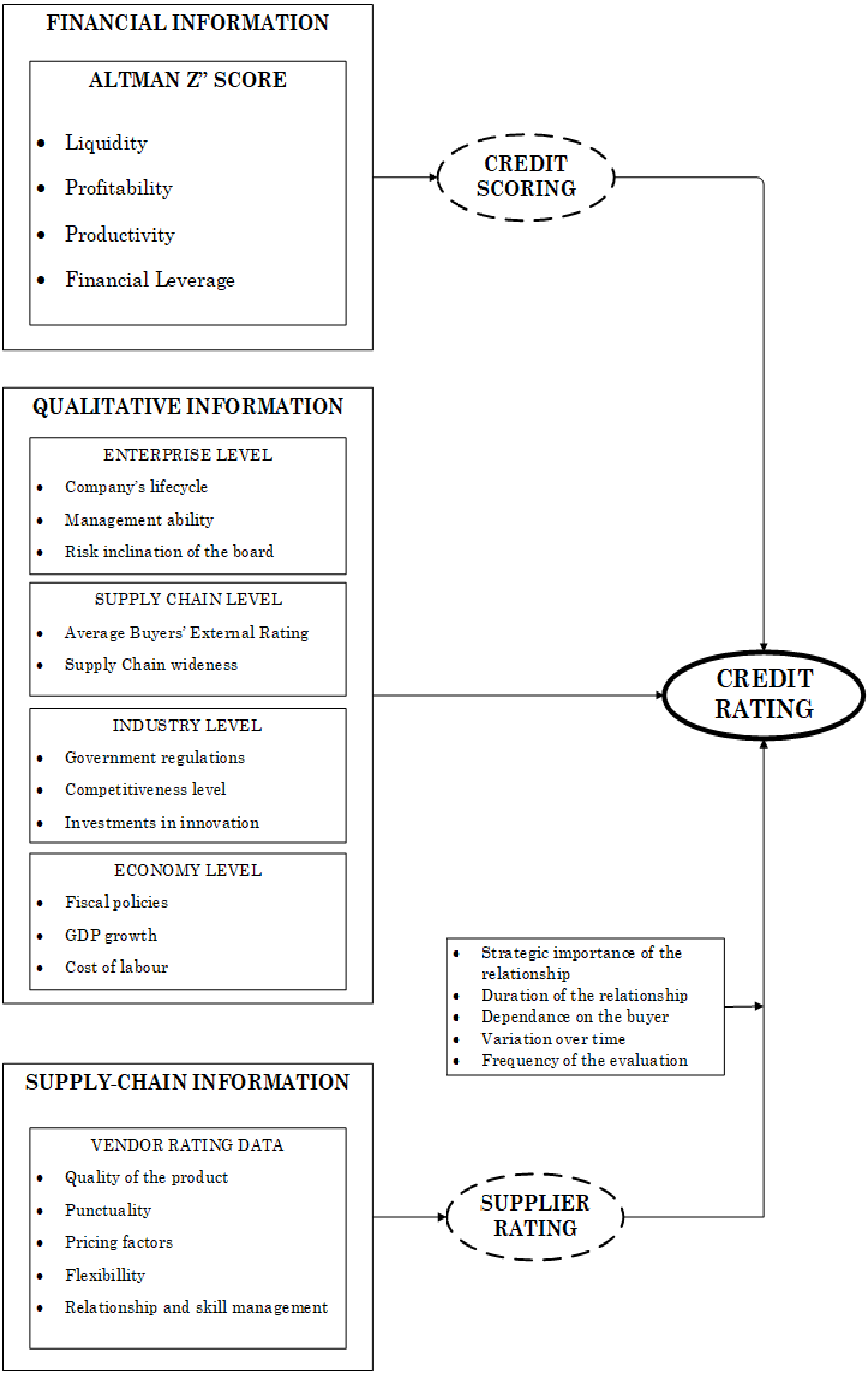

Figure 0.6 Supply-chain oriented credit rating framework

First, the financial dimension remains the most important source of information of the framework since financial ratios look at many aspects of a business. In the framework, the Z"-Score of Altman has been selected as the reference for the financial dimension. This choice has been made because we demonstrated in the first research question that it is highly correlated with the BPER rating. The Z"-Score is particularly suitable to firms not traded publicly and to non-manufacturing entities, which are the companies that could have greater advantages from a new and more integrated credit scoring framework. In fact, big companies with consolidated financial structures easily have great performances in the financial dimension and, so, in the credit rating since it is deeply influenced by that dimension. Vendor rating data represent the innovative perspective introduced by this research. RQ1 demonstrated that the information coming from vendor rating systems and the financial ratios are inconsistent between each other. In RQ2, the focus group have developed a framework to determine whether a company has good operating performances or not. As already discussed, it is important to include this dimension in or analysis since financial information gives only a partial view of the creditworthiness of a company.

However, the impact that supplier rating has on the final determination of credit rating is driven by some variables:

- **Strategicity of the relationship**: the more strategic are the relationships that are rated, the more weight they have in the determination of credit rating. On the contrary, vendor rating scores coming from casual or spot relationships would not affect the assessment.
- **Duration of the relationship**: vendor rating evaluations produced in long-lasting relationships are more likely to provide significant insights about the company actual operative performance.
- **Dependence on the buyer**: the more a supplier is dependant on a single buyer (i.e. most of the revenue shares are given by a single buyer), the more creditworthiness analysis should be sensitive to possible fluctuations of those ratings.
- **Variation over time**: the more a supplier rating fluctuate in the same time horizon, the more its further analysis is worth it. In fact, a "flat" supplier rating trend would not provide many signals about potential alerts.
- **Frequency of the evaluation**: the more frequent and complete supplier rating are, the more reliability they have in the determination of credit rating.

The last piece of the puzzle is represented by the qualitative information that banks and financial institution evaluate when assessing creditworthiness of a borrower. After financial information and vendor rating information, more qualitative information needs to be included as well. Qualitative information can focus on different levels: *enterprise, supply-chain, industry and economy.*

Conclusions

This research has provided several contributions to future studies on this theme. Thanks to a structured approach, this work has systematically analyzed and responded to the requirements of each research question.

In particular, the following insights can be taken away from this research:

- Credit scoring models represents a good "proxy" of the credit rating models produced by financial institutions. The high correlation between these two dimensions is a signal that financial information is still one of the main driver used to develop a credit rating model. Thus, companies' creditworthiness deeply depends on their financial performances, while more qualitative aspects play a secondary role.

- Altman's Z"-Score model has the highest correlation coefficient with the credit rating provided by BPER Banca. This result is not surprising because this model was designed to assess SMEs which are the main part of the sample provided by BPER Banca;

- Vendor rating data represents a piece of information that is currently missing in credit rating models. In fact, if we consider separately the financial and the operational dimensions, they often give different judgments about the creditworthiness of a company. More than 50% of the companies under show inconsistent values in those two dimensions. Thus, the variability of the vendor rating data is not "explained" by the financial dimension.

- The integration of the vendor rating perspective in the creditworthiness process can increase the effectiveness of credit rating models. In fact, vendor rating data can act as "weak signal" thanks to their anticipatory behavior. Furthermore, lending institutions would have a more complete picture of the borrower since financial information are sometimes too restrictive.

- The main benefit coming from the integration of financial and operational information is the lower risk exposure that banks and financial institutions would face. In this way, a better planning of capital requirement can be executed, ensuring financial stability.

- Suppliers would benefit from the adoption of this integrated approach thanks to a more complete definition of their creditworthiness situation.

Future developments

Our results have theoretical relevance and can be used as foundation for the practical development of a new supply-chain oriented credit scoring model. This paragraph aims to show two key requirements that data must meet to ensure the creation of this innovative credit scoring model.

Presence of defaulted companies

This is the first fundamental assumption that must be met when a new default predictive model is developed. The key is being able to discriminate between defaulted and active companies.

In particular, it is necessary that the sample can be unequivocally split into two clusters, according to insolvency status: companies that went bankruptcy on one side versus companies that did not went bankruptcy, in a certain year *t*. This parting is extremely important because, if the model aims to predict reality, it needs to be designed based on real outcomes. In this way, the performances of the model can be assessed on the comparison between predicted default status vs real default status.

Our recommendation for future studies is that researchers must accurately design the data collection process, which is the fundamental step to develop a good-performing credit scoring model.

Presence of historical vendor rating data

A further requirement that data must have to obtain a reliable predictive model is complete historical records for each of the variables taken into account. In particular, this is a complicated process when considering vendor rating variables. Differently from financial data, the collection and disclosure of vendor rating data is not mandatory. Thus, it is not uncommon to have partial historical records of vendor rating data.

In fact, a predictive model is evaluated on two-key aspects: *accuracy* and *predictive time horizon power*. The former is about how good the model is in discriminating between good and bad companies, while the latter represents how timely the model is in predicting default of a company. In fact, *ceteris paribus*, a model that is able to predict earlier the default of a company is considered a better model. To do so, the accuracy of predictive model must be analyzed backwards in time. The more a model is able to predict default throughout the years moving from the present to the past, the more the model is reliable.

CHAPTER 1 - CREDIT RATING

In this chapter, the attention is given to the notion of *creditworthiness* in the risk assessment vision. The financial crisis of 2007 and the consequent limited access to capital made this issue very popular. It is fundamental to understand how banks and other financial institutions assess the creditworthiness of a company, because this decision affects its day-by-day activities. Thus, the credit rating models need to be as more accurate and reliable as possible in order to assess credit risk in a precise way. A more trustworthy system would bring advantages both for companies and for financial institutions. In the beginning of the chapter, some theoretical definition will be given. After that, the focus will shift on how the issue of creditworthiness has evolved during time. The last paragraphs will explore the concept of credit rating model pointing the attention on the most popular statistical models. In this section, it will be also evaluated whether a financial approach is enough to evaluate credit risk or a new vision is needed.

1.1 Creditworthiness and Credit Risk

Creditworthiness can be defined as "a presumed ability to meet agreed deadlines related to repaying the credit and the interest accrued without affecting the vitality of the borrower, i.e. the repayment process should be based on the income received in the process of the borrower's usual activity, without affecting adversely his financial situation, his financial results as well as other business entities" (Feschijan, 2008). It represents the economic and financial reliability of a subject and it affects the financial risk related to a supply of credit in his favor. Banks use it in order to assess the level of risk of its possible clients. Creditworthiness is usually measured through a credit rating score which considers various aspects of the company to determine its risk of default. For example, a lower credit score corresponds to a higher cost of capital and it influences the kind of guarantees that a lender requires to a borrower in order to issue a new loan. There is not a common rule to assess the creditworthiness of a company but there are some aspects that are always to be considered, such as: the debt ratio, the liquidity, the presence of previous insolvency and the availability of different financial resources. Checking the creditworthiness of companies is helpful to establish a new credit relationship, to increase the amount of credit and to monitor the credit situation of companies preventing difficulties coming from a worsening of their creditworthiness. Creditworthiness is deeply influenced by the economic situation either of the industry and of the country where the company operates.

The notion of creditworthiness is strictly connected with the concept of *Credit Risk*, which is defined as the probability that one of the two counterparts of a contract doesn't meet its obligations and create a loss for the borrower (Ammann, 2001). In other words, if the credit can be defined as "nothing but the expectation of a sum of money within some limited time", then credit risk is the chance that this expectation will not be met. A change of the creditworthiness of a company is related to another change in its credit risk. This change can be caused by the sudden default of the borrower or by the downgrading of its creditworthiness. Banks monitor day-by-day its borrowers in order to instantaneously assess their credit risk.

Managing credit risk is the core activity of banks since their born in Florence about seven hundred years ago, but has become popular only after the second half of the twentieth century. In fact, a lot of historical events occurred at that time: the protests of 1968[1] led to an increase of the labor cost moving the production of labor intensive goods in emerging countries, the 1973 and 1979 oil crisis'[2] made the world more economical unstable, the Bretton Woods Era[3] ended leading to the creation of a floating exchange rate system. Due to these events, an economic uncertainty was spread all over the world, from Mexico to Russia. In this period of economic turbulence, United States banks started to develop models that could determine the creditworthiness of a company and so, its credit risk. Parallelly, regulatory institutions started to study this issue providing new instruments and tools.

1.2 The Basel accords

The Basel accords– Basel I, Basel II and Basel III – are a set of banking regulations in the banking industry set by the Basel Committee on Bank Supervision (BCBS). They provide banks with recommendations on capital risk, market risk and operational risk. The aim of these accords is to ensure that financial institutions have enough capital on account to meet obligations and absorb unexpected losses. The Basel Committee on Bank Supervision was founded in 1974 and it consisted of representatives from central banks and regulatory authorities of the *Group of Ten* countries plus Luxemburg and Spain.

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[1] The protests of 1968 comprised a worldwide escalation of social conflicts, predominantly characterized by popular rebellions against military and bureaucratic elites, who responded with an escalation of political repression.

[2] The 1973 oil crisis began in October 1973 when the members of the Organization of Arab Petroleum Exporting Countries proclaimed an oil embargo. The 1979 oil crisis or occurred in the United States due to decreased oil output in the wake of the Iranian Revolution.

[3] The Bretton Woods system of monetary management established the rules for commercial and financial relations among the United States, Canada, Western Europe, Australia and Japan after the World War II.

Nowadays the membership has been increased to 27 members. The Basel Committee on Bank Supervision specify that its original goal is the enhancement of “"financial stability by improving supervisory knowhow and the quality of banking supervision worldwide”. It only provides recommendations to member countries because it doesn’t have the authority to impose its decisions. However, most member countries and, even, some unmember ones decide to implement the Committee’s policies thought regulations and national laws.

1.2.1 Basel I

During the savings and loan crisis[4], banks were lending extensively and countries were increasing their external indebtedness at unsustainable rates. At that time there was no regulations on this matter, so the Basel Committee on Banking Supervision decided to intervene in order to prevent the risk of bankruptcy of the major international banks.

In 1988, the Basel Committee on Bank created the Basel I capital Accord with the purpose of set up a fail and stable international banking system. The focus was on capital risk and the main aim was to enforce minimum capital requirement. To define the minimum amount of capital that a bank should hold a definition of capital was needed. Thus, the Basel Committee on Banking Supervision defined capital on two tiers:

- *Tier 1 (Core Capital)* includes declared reserves and stock issues.
- *Tier 2 (Supplementary Capital)* includes all other source of capital.

Basel I defined credit risk as the risk weighted asset (RWA) of a bank, in other words the assets of the bank are weighted in relation of their relative credit risk. The accord, also, stated that the total capital of a bank should be at least the 8% of the RWA.

[4] The Savings and Loan (S&L) Crisis began under the volatile interest rate climate of the 1970s, when vast numbers of depositors removed their money from the S&L institutions and deposited it in money market funds. This allowed for higher interest rates, because the funds were not regulated

$$Risk\,Weighted\,Asset = \frac{Capital\,requirement}{\left(\sum_{i=0}^{n} A_i \alpha_i\right)} \geq 8\%$$

Where:

Capital requirement is the amount of capital a bank or other financial institution must hold as stated by Basel I;

A_i represents the asset *i;*

a_i represents the level of risk of the asset *i*.

Risk Weight	Asset Class
0%	Gold. cash, central bank and government debt, and any Organization for Economic Cooperation and Development (OECD) government debt
20%	Development bank debt, OECD bank debt, OECD securities firm debt, non-OECD bank debt (under one year of maturity), non-OECD public sector debt and cash in collection
50%	Residential mortgages
100%	Private sector debt, non-OECD bank debt (maturity over a year), real estate, plant and equipment, and capital instruments issued at other banks.

Table 1.1 Classification of Asset classes as defined by Basel I

However, this command-and-control style of regulation lefts the banks free to act and organize their credit activities as they wished in accordance with the requirement. For this reason, some critics have been moved toward Basel I during time (Zaher, 2010):

- This accord was focusing only on credit risk without considering the market risk that was introduced then in Basel II
- The bad classification of risk towards private companies that were accounted with the maximum level of risk without considering their creditworthiness.

- The relationship between maturity and credit risk was not deeply analyzed. In fact, the credit risk grow as the time horizon becomes bigger because of the possibility that a company could receive a downgrade of its creditworthiness.
- Basel I assumed a common market to all actors, which is obviously not true. There is no consideration of the macroeconomic risk and of the risk associated to the different currencies.
- The 8% assumption is a static measure of the default risk. It does not consider the evolution of default risk during time.
- There is no consideration of the portfolio diversification effect. Usually a more diversified portfolio is less risky of a correlate one because it does not depend of a single industry.

Basel I was the first international instrument aimed to assess capital in relation to credit risk. It also launched the trend towards risk modelling researches and despite the great importance of SMEs in the economy, the default analysis of SMEs was not explored in depth before the introduction of the new Basel rules (Edmister, 1972; Keasey and Watson, 1987; Laitinen,1992; Claessens et al., 2005). Basel I remains a milestone in the banking and finance history, even if there were some pitfalls-

1.2.2 Basel II

"*Basel II is not intended simply to ensure compliance with a new set of capital rules. Rather, it is intended to enhance the quality of risk management and supervision*."

Jaime Caruana
Former Chairman of Basel Committee
Governor of the Banco de España

Basel II, also called Revised Capital Framework, was published in 2004 by the Basel Committee on Bank Supervision to address new risks that had arisen in the world of banking. The main motivation of Basel II was the globalization of financial markets, there was the need to create coordinated international regulations. Basel I was under criticism because the calculation of credit risk was "roughly and imprecise" (Hermann, 2001). The banking environment was changing, trading activities and banks market prices were growing in importance. New financial instruments and methods of credit risk management such as derivate and collaterals were used in banks' everyday activities arose a need of innovation in the regulations. The Basel Committee on Bank Supervision started to discuss a new regulation model in 1999. The main objective of Basel II was to align banks' regulatory capital more closely with their risks, taking account of progress in the measurement and management of risk and of the opportunities which these provide for strengthened supervision (Cornford, 2005). Basel II is based on three pillars:

- *Minimum Capital Requirements*: this pillar is derived by Basel I. The definition of Capital, as well as the minimum capital ratio of 8%, were not changed. However, two new typologies of risk where introduced: Operational Risk and Market risk. Operational risk is defined as "the risk of direct or indirect loss resulting from inadequate or failed internal processes, people and systems or from external events"[5]. Market risk is that of loss resulting from changes in the market value of its assets before the positions in question can be offset or liquidated (Cornford, 2005).
- *Supervisory Review*: it represents the biggest innovation since Basel I. It explains what the banks' supervisors in each country must verify and authorizes it to raise the minimum capital requirements applicable to a bank if they were not satisfied with its responses or practices (Chiapello, 2016)
- *Market Discipline*: it defines all the information that must be disclosed by banks in order to enable "the market" to make informed decisions (Baud, 2016).

[5] Definition provided by the Basel Committee on Bank Supervision.

The Basel Committee on Bank Supervision moved from the one pillar model of Basel I to the three pillars model of Basel II. The new regulation had no more a command-and-control style, but it was created to facilitate market control and rewards (Chiapello, 2016). Basel II also introduced the key concept of Rating System, defined as *"the set of the methods, processes, controls, data and information systems that support the assessment of credit risk, the assignment of internal worthiness degrees and to the quantitative estimation of defaults and losses"*.

In fact, one of the most important development made by Basel II is on credit risk. The Basel Committee, in fact, developed two approaches to evaluate regulatory capital for credit risk: the standard method (based on external ratings) and the IRB method (based on internal ratings). The *Standard Method* followed the same principles of Basel I. The major difference between Basel I and Basel II is that the risk-weights were no longer based on institutional criteria (OECD or non-OECD countries) for states and banks and it was no more assigned the standard weight of 100% to enterprises. With Basel II the evaluation of risk-weights for assets is provided by credit rating agencies. The private rating agency world was dominated by three main actors which received an official accreditation for this purpose: Moody's, Standard & Poor's and Fitch Ratings. Each country had also the possibility to accredit local agencies[6]. A lower weight was assigned to higher credit ratings which means a lower capital requirement[7]. Basel I assigned more favorable weight to OECD members and to their banks, it was not an equal system (Van Roy, 2005). Evaluating weights based on credit rating agencies created a more trustful and equal system. However, this system is not completely independent by the actions of the states since they still define the risk weight associated to each of the scores of the credit rating agencies. On the other hand, there is the *IRB method* which allowed banks to develop their own internal rating system to determine the risk weights of the assets. The Basel Committee stated that *"Internal risk ratings are an important tool in monitoring credit risk. Internal*

[6] For example, France approved the COFACE and the Banque de France's rating systems.

[7] 0% for a state rated AAA, 20% for a bank rated AAA, but up to 150% for an enterprise rated lower than B-

risk ratings should be adequate to support the identification and measurement of risk from all credit exposures, and should be integrated into an institution's overall analysis of credit risk and capital adequacy". These internal rating systems had to be approved by the supervisory authorities and had to satisfy specific requirements. In this way, banks have been able to autonomously determine the creditworthiness of a subject and its probability of default[8].

Basel II overcame some of the limits of the previous accord, but it still presented some pitfalls:

- Small banks had difficulties in collecting information and tools to develop efficient methods to assess credit risk. This created a discrimination between big and small banks.
- Internal ratings penalize SME because banks are tempted to consider them as riskier in order to increase their interest rate.
- The "pro-cyclical process". Due to it if there is economic boom in the country then banks require less capital for recovering the risk but in case of down of economy then banks require more capital for recovering the risk (Udeshi, 2004).
- External credit rating provided institutions became more important. This create the problems like the external institutions mispriced the risk due to conflicts of interests (Teply, 2010).

1.2.3 The financial crisis of 2007 and the Credit Crunch

"When the music stops… things will be complicated. But as long as the music is playing, you've got to get up and dance. We're still dancing."

Chuck Prince
CEO of Citigroup

[8] A definition of default is given by the Basel Committee. A subject is in default if one of these two conditions arises: first if the bank determines that the borrower is unlikely to pay its obligations to the bank in full, without recourse to actions by the bank such as the realization of collateral; second if the borrower is more than 90 days past due on principal or interest on any material obligation to the bank.

These words were pronounced by Chuck Prince on July 8, 2007, and almost one month later the "music stopped" (Blinder, 2013). On 9 August 2007 BNP Paribas announced that it was ceasing activity in three hedge funds that were specialized in US mortgage debt. This was the moment in which it became clear that there were trillions of dollars of derivatives which were now worth a lot less than the bankers had previously imagined. The amount of losses, such as the exposure of individual banks, was not known, so immediately trust disappeared by the banks stopped doing business with each other. Adam Applegarth, former boss of Northern Rock, called this day *"the day the world changed"*. This was the first step of the financial crisis of 2007 that led the world in the most severe crisis since the Great Depression (Brunnermeier, 2008). After an incredible growth, the US financial system experienced a "perfect storm" during the years 2007-2009 (Blinder, 2013). The economist Alan Blinder identified seven key weaknesses that anticipate the crisis:

- Inflated asset prices, especially of houses[9] but also of certain securities[10];
- Excessive leverage (heavy borrowing) throughout the financial system and the economy;
- Lax financial regulation, both in terms of what the law left unregulated and how poorly the regulators performed their duties;
- Disgraceful banking practices in subprime and other mortgage lending;
- The crazy-quilt of unregulated securities and derivatives that were built on these bad mortgages;
- The abysmal performance of the statistical rating agencies, which helped the crazy-quilt get stitched together;
- The perverse compensation systems in many financial institutions that created powerful incentives to go for broke.

[9] The housing bubble

[10] The bond bubble

In a year 8 trillion of dollars of US stock market wealth were lost, banks were forced banks to write down several hundred billion dollars in bad loans caused by mortgage delinquencies and the stock market capitalization of different banks dramatically fell. All of what specified above brought to a huge contraction of credit. On one side, households and firms stopped to ask for loans causing a drop in the demand side, on the other side, as we said banks stopped to lend to each other causing a drop also in the supply side. Economists call this situation of absence of liquidity in the market as *Credit Crunch*. Clair and Tucker (1993) used this word to depict a situation of lack of credit supply due to a decline in the value of bank capital and to the introduction of new rules by regulators that require banks to hold more capital as before. In other words, a credit crunch is an economic condition that occurs when it is difficult to obtain investment capital. It is usually an extension of a recession, banks are so scared by bankruptcies and defaults that stop to lend funds causing an increase of the price of debt. The 2007-2008 credit crunch, also called credit squeeze, has been far more complex than the previous ones (Mizen, 2010) due to the financial innovation that led to innovative ways of packaging and reselling assets. The credit crunch was sided by a lack of liquidity, so central banks decided to provide funding liquidity for distressed institution and market liquidity[11]. To contrast the credit crunch, the Federal Reserve[12] reduced the discount rate to 5,75% on the 17 August of 2007 warning that the credit crunch could have been a risk to economic growth. However, the banks were still fearing a lack of creditworthiness in the interbank market, so the FED decided to cut its main interest rate by half a percentage point to 4.75%. Again, on September 18. On the 22nd of January 2008, the FED did the biggest cut of rates in 25 years lowering them to 3,5% and trying to prevent the recession of

[11] "Funding liquidity" refers to the ease of access to external finance and depends on the characteristics of the borrower. When a borrower is not regarded as creditworthy, it may face higher borrowing osts and quantity restrictions that present a funding problem; this will need to be resolved by borrowing from nonmarket sources, and in the case of a bank, from the central bank. Market liquidity is a property of the relative ease with which markets clear at a fair value. When markets become very thin, the authorities may intervene to ensure they are able to clear, by for example "making the market"
by accepting certain assets in exchange for more liquid ones.

[12] The Federal Reserve System is the central banking system of the United States.

the economy. Central banks all over the world continued to cut their interest rate to inject liquidity in the market, on the 16th of December 2008 the FED slashed its key interest rates to a range from zero to 0,25%.

Figure 1.1 US discount rate (2000-2010)

The main reason of these actions was to avert the risk of an economic depression and to counter deflationary pressures (Cœuré, 2013). Moreover, the cut of interest rates was trying to favor borrowers contrasting the increase in borrowing costs caused by the widening of financial spreads. During the same period, the return on safe financial assets was very low: on one hand savers that were looking for safe investments had to accept low rates of returns (even negative ones due to the inflation) and on the other hand asset prices grew rapidly because of the low interest rates favoring households and firms with a positive net worth. Benoît Cœuré, Member of the Executive Board of the ECB explained that the choice was between helping borrowers and supporting lenders, and central banks decided to support the first group. In this period of uncertainty and lack of liquidity, there was the need to revise the banking system in order to strengthen the capital requirements for banks to prevent banks from collapse by taking excessive risks. This revised banking system was created by the Basel Committee with Basel III.

1.2.4 Basel III

The financial crisis of 2007 pushed to the limit the banking systems proving that international banks still fell short of capital and were not be able to fully absorb credit losses. The first version of Basel III was published by the Basel Committee on Banking Supervision in 2009. It was a direct response to the credit crisis previously discussed; the main business goals of Basel III were to improve the regulation, the supervision and the risk management processes of the banking sector. Basel III sought to foster greater flexibility at bank level in order to reduce the risk of system-wide shocks. This was achieved through an improvement of the quality of capital ensuring that the excessive risky assets were to be eliminated for the safety of customer and of the banking system in general. Basel III continued to be based on three pillars: *Minimum Capital Requirement*, *Supervisory Review Process* and *Market Discipline*. The major changes proposed by Basel III are:

- Basel III introduced tighter capital requirements in comparison to Basel I and Basel II because the definition of regulatory capital previously provided had some flaws that allowed banks to display strong solvency ratios with limited tangible common equity. Increasing the quality of capital lead to a higher loss absorbing capacity of banks. In this way banks became more solid and more able to deal with period of financial stress.
- Basel III asked bank to keep a capital conservation buffer of 2,5% that can be used to absorb losses during financial crisis.
- One of the key elements of Basel III is the introduction of the countercyclical buffer. This buffer has the objective of increasing capital requirements in good times and decreasing them in bad times. It tries to avoid the risk of a credit crunch encouraging lending during financial crisis. Banks hold a countercyclical buffer that range from 0% to 2,5%.

- The minimum capital requirement remains at the level of 8% as stated by the previous Basel accords. However, the total capital requirement increases to 10,5% due to the presence of the countercyclical buffer.
- Basel III introduced leverage and liquidity requirements to ensure that the banks have sufficient liquidity during economic and financial crisis. Minimum leverage ratio[13], Liquidity Coverage Ratio (LCR)[14] and Net Stable Funding Ratio (NSFR)[15] have been introduced.

1.3 The components of Credit Risk

In chapter 1.1, credit risk has been defined as the possibility of an unexpected change in the creditworthiness of a subject which is financially exposed. In chapter 1.2 the research has given an historical background of the evolution of this concept over the time. In this chapter, the different components of credit risk will be discussed and the IRB approach provided by Basel II will be further investigated. It is important for a bank to continually monitor the financial situation of its customers in order to estimate the expected loss (EL), which is not considered as a risk, and the unexpected loss (UL), which is the real source of risk.

1.3.1 Expected Loss

On one hand, banks cannot forecast all the losses that they will suffer in a certain year, but, on the other hand, banks can evaluate in advance the level of credit losses that they are reasonably going to face in that certain year. These computable losses are called *Expected Loss* which are seen by financial institution as a cost component of doing business. Banks manage them in many ways, including through the pricing of credit exposures and the provisioning. Basel II introduced the IRB approach to credit risk that can be used by bank to estimate

[13] High-quality assets must be above 3% of all total assets.

[14] It refers to highly liquid assets held by financial institutions to meet short-term obligation

[15] It measures the amount of longer-term, stable sources of funding employed by an institution relative to the liquidity profiles of the assets funded and the potential for contingent calls on funding liquidity arising from off-balance sheet commitments and obligations.

calculate the Expected Loss and, so, to determine the capital requirements for a given exposures, as shown by the following formula.

$$EL = PD \times LGD \times EAD$$

Where:

- PD is the Probability of Default;
- LGD is the Loss Given Default;
- EAD is the Exposure at Default.

Respect to the external rating approach, the IRB method has two main advantages: *"The first is additional risk sensitivity, in that a capital requirement based on internal ratings can prove to be more sensitive to the drivers of credit risk and economic loss in a bank's portfolio. The second is incentive compatibility, in that an appropriately structured IRB approach can provide a framework which encourages banks to continue to improve their internal risk management practices"* (Consultative document issued by the Basel Committee on Banking Supervision, 2001).

Probability of Default

Basel II defined the *Probability of Default* as the likelihood that a loan will not be repaid and, so, falls into default. There are two ways to evaluate it. On one side, default probabilities can be evaluated from market data: the most used model is the one created my KMV Corporation[16] called *Expected Default Frequency*. On the other side, default probabilities are calibrated from the rating classes. Ratings can be provided either by credit rating agencies, such as Moody's, Standard & Poor's and Fitch, or by internal ratings of banks.

Loss Given Default

Loss Given Default is defined by Basel II as *"the percentage of exposure the bank might lose if the borrower defaults"*. In formula, LGD is:

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[16] KMV Corporation is a leading provider of quantitative credit analysis tools to lenders, investors, and corporations. It was acquired by Moody's Analytics in 2002.

$$LGD = 1 - RR$$

Where RR is the Recovery Rate[17]. RR is deeply influenced by the characteristics of the actor who defaulted, by macroeconomics factors and by the characteristics of the debt issuer.

There are three different approached that can be used to measure the Loss Given Default:

- *Market LGD*: It is used for defaulted bonds and loans that are traded in the market. One can observe the prices of these financial instruments at the time when the trade is occurring. Rating agencies often use this approach. Moody's observes the price one month after the first occurrence of default. This price reflects the sentiment of the market at that time. For Example, if a defaulted bond is traded in the market at 30 cents per one dollar of capital, the recovery rate is 70%. A problem of this approach is that can be used only with the financial exposures that have a secondary market.
- *Workout LGD*: It is estimated from the historical information observed in the entity, by discounting the flows that are recorded throughout the recovery process of the contracts in default at a certain time. If the historical experience is not sufficient to make a reliable estimation, external sources have to be used.
- *Implied Market LGD*: This approach looks at credit spreads on the non-defaulted risky bonds currently traded in the market. This is an innovative approach that is not very diffused in the banking world, rating agencies use it as a check against the classic approaches.

The Loss Given Default is strictly correlated with the Probability of Default. During financial crisis, for example, the Probability of Default usually increase causing a decrease of the Recovery Rate. In the same way, if an industry faces a decrease of revenues due to the obsolescence of its products, the Probability

[17] The recovery rate can be defined as the amount recovered through foreclosure or bankruptcy procedures in event of a default, expressed as a percentage of face value.

of Default increase, while the value of plants and inventories fell down such as the Recovery Rate.

Exposure at Default

The Exposure at Default is defined as *"the uncertainty on the exact amount at risk at the very moment of a future default is*" (Van Gestel and Baesens, 2009). Exposures can have certain or uncertain value. On one side, those of a certain value are the ones for which the bank knows the exact amount of the granted loan, on the other side, those of an uncertain value are the ones where the amount is not quantifiable until the manifestation of the insolvency. The Exposure at Default of a current account can be mathematically evaluated in this way:

$$EAD = DP + UP \times CCF$$

Where:

- DP is the Drawn Portion of the current account;
- UP is the Undrawn Portion of the current account;
- CCF is the Credit Conversion Factor that represents the percentage of the amount of current account that debtor will use after the insolvency.

1.3.2 Unexpected Loss

As previously specified, the losses that the bank reasonably expects to face in a certain period of time are called Expected Losses (EL) and they are shown in the graph by the dashed line.

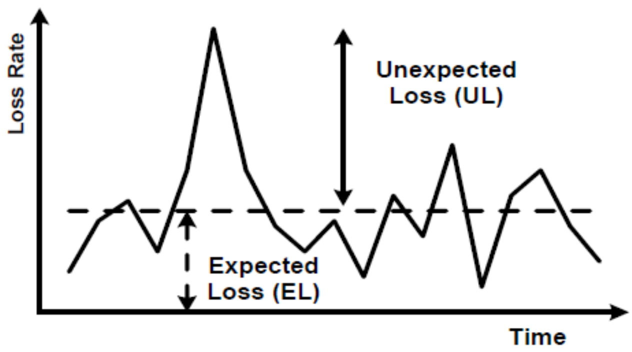

Figure 1.2 Unexpected Loss and Expected Loss during time

However, a bank can also face peak losses that exceed expected levels, such losses are called Unexpected Losses (UL) and they are shown by the black line above the expected losses. Banks are usually protected by unexpected losses through the capital that has a loss-absorbing function and provides a buffer against those peak losses. It is impossible to forecast Unexpected Losses, but a bank needs to be prepared to these peeks since they can be very large. Some tools, such as the interest rate, can be used to absorb a part of these unexpected losses, but it is not possible to set up a price that cover all the unexpected losses since there would be no market for it. The worst scenario that a bank could face is that losses are equal to its entire capital. Even if this event is unlikely, banks deal with a trade-off between the amount of capital and of profits. On one hand, banks always try to hold as less as possible capital to free economic resources that can be directed to profitable investments, but, on the other hand, banks cannot risk not to meet their debt obligations and, so, to become insolvent due the setup of a thoughtless level of capital.

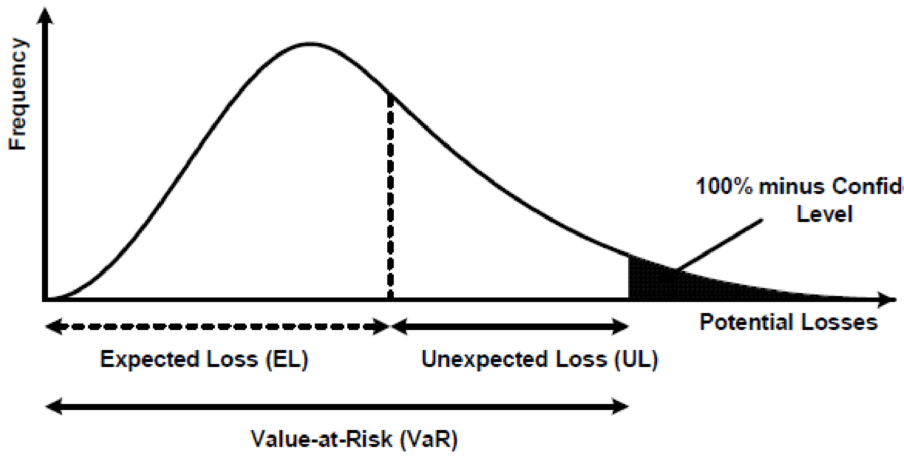

Figure 1.3 Likelihood of losses of a bank

Basel II provided a framework that is based on the frequency of bank insolvencies that policymakers are willing to accept[18]. The curve in the figure describes the likelihood of losses of a certain magnitude. Small losses around Expected Loss occur more frequently than large ones. The likelihood that a bank will not be able to meet its own debt obligations through profit and capital is equal

[18] The area under the entire curve is equal to 100% (i.e. it is the graph of a probability density).

to the black area on the right. This is the probability that the sum between Expected Loss and Unexpected Loss is minor that the total losses. 100% minus this probability is called the confidence level and the related threshold is called Value-at-Risk (VaR) at this confidence level. The likelihood that a bank remains solvent within a given time frame (One year for the Basel Accords) is equal to the confidence level if the bank set up the capital according to the gap between Expected Losses and the Value-at-Risk threshold. Basel II stated that capital needs to be maintained at a fixed confidence level.

1.4 Credit Rating

1.4.1 What is it?

Once defined what creditworthiness and credit risk are, it is important to focus on the concept of *Credit Rating*. In chapter 1.2.2 the definition of Basel II was given, but, commonly, credit rating is defined as an assessment of the creditworthiness of an entity respect to a particular financial obligation or in general terms. Credit rating can be evaluate internally by banks or externally by credit rating agencies; there are around 150 of them, but the three largest one, called “The Big Three”, are Standard & Poor’s Ratings Services, Moody’s Investors Service and Fitch Ratings[19]. In the Table 1.2, the International Monetary Fund[20] collected how “the big three” regard their ratings.

[19] They share roughly 95 percent of the market. Standard & Poor’s Ratings Services and Moody’s Investors Service have 40 percent of the market while Fitch Ratings holds 15 percent (White, 2010)

[20] The International Monetary Fund (IMF) is an international organization headquartered in Washington, D.C., of "189 countries working to foster global monetary cooperation, secure financial stability, facilitate international trade, promote high employment and sustainable economic growth, and reduce poverty around the world."

Fitch	"Credit ratings express risk in relative rank order, which is to say they are ordinal measures of credit risk and are not predictive of a specific frequency of default or loss. Fitch Ratings' credit ratings do not directly address any risk other than credit risk, ratings do not deal with the risk of a market value loss on a rated security due to changes in interest rates, liquidity and other market considerations."
Moody's	"There is an expectation that ratings will, on average, relate to subsequent default frequency, although they typically are not defined as precise default rate estimates. Moody's ratings are therefore intended to convey opinions of the relative creditworthiness of issuers and obligations...Moody's ratings process also involves forming views about the likelihood of plausible scenarios, or outcomes—not forecasting them, but instead placing some weight on their likely occurrence and on the potential credit consequences. Normal fluctuations in economic activity are generally included in these scenarios, and by incorporating our views about the likelihood of such scenarios, we give our ratings relative stability over economic cycles and a sense of horizon."
Standard & Poor's	"Standard & Poor's credit ratings are designed primarily to provide relative rankings among issuers and obligations of overall creditworthiness; the ratings are not measures of absolute default probability. Creditworthiness encompasses likelihood of default and also includes payment priority, recovery, and credit stability."

Table 1.2 - Table 1.2 Definiton of credit rating by the The Big Three

Credit ratings are usually expressed in a scale of letters and figures. The big three convey the credit rating as stated in the following table:

Interpretation	Fitch and S&P	Moody's
Highest quality	AAA	Aaa
High quality	AA+	Aa1
	AA	Aa2
	AA–	Aa3
Strong payment capacity	A+	A1
	A	A2
	A–	A3
Adequate payment capacity	BBB+	Baa1
	BBB	Baa2
	BBB–	Baa3
Likely to fulfill obligations, ongoing uncertainty	BB+	Ba1
	BB	Ba2
	BB–	Ba3
High-risk obligations	B+	B1
	B	B2
	B–	B3
Vulnerable to default	CCC+	Caa1
	CCC	Caa2
	CCC–	Caa3
Near or in bankruptcy or default	CC	Ca
	C	C
	D	D

Table 1.3 Fitch, S&P and Moody's different scales of credit rating

Thanks to credit ratings, the concepts of risk and returns are linked. For example, an investor looks at the ratings to assess the risk level of a target asset and to compare its offered rate of return with the expected one in order to maximize its returns. If credit ratings didn't exist, the investor would take the decision whether to buy a certain asset or not only considering its familiarity with it. It is clear that this would not be an optimal situation. In the banking world, the credit rating affects not only the decision on whether a loan should be approved for a borrower or not, but its credit rating also defines the interest rate at which that loan have to be repaid. Credit rating agencies serve different functions:

- *They provide unbiased opinion.* Even if this aspect nowadays is often challenged by the public opinion, credit rating agencies should provide an unbiased opinion because they don't have interests in the companies that they evaluate.
- *They provide quality and dependable information.* The information provided by credit ratings agencies are reliable because they are developed by trained and professional staff who has access to a lot of data that are not publicly available.
- *They provide information at low cost.* Investors can easily access to the rating assigned by credit rating agencies when taking their decisions. Ratings are available in form of reports at negligible price.
- *They provide easy to understand information.* As previously discussed, ratings are published in scale of letters, an easily comprehensible way.
- *They provide basis for investments.* Most of the investors rey on ratings while taking investments decisions. They use ratings to estimate credit risk and, so, the return associated.
- *They enhance corporate image.* If a company receive a high rating, its public image grows.

1.4.2 How is it evaluated?

Once defined what a credit score is, it is important to define how it is evaluated and what kind of information are usually included in its determination. The assessment of the credit risk is mainly based on the analysis of the financial risk, but also a wide range of factors are considered, even if with a lower weight. In fact, factors, as industry risks, business risks and management skills, can have an impact on the debtholder ability to repay its obligations. The aim of this paragraph is to identify the key criteria used by analyst in the credit rating process. Banks and credit rating agencies does not publicly disclose their formulas to evaluate credit risk. However, their ratings are usually consistent among themselves since the same criteria are examined. Each bank or credit rating agency tend to vary only in their weighting of the individual parts of the credit analysis. Since there is not a single way of assessing a credit rating, the one that is explained in the following lines has been provided by ABI[21]. Assessing the credit rating of a company means determining the issuer's ability to repay its obligations in full and in time. Since most of the debt instruments require he repayment of interest and principal over time, the credit analysis will focus on the company's ability to generate sufficient cash to fund business operations and service debt obligations. Thus, the key determinants of the credit rating are the financial flexibility of the company and its ability to generate free cash flow from operations. Those determinants are conditioned either by quantitative and qualitative factors. In fact, the credit rating is based on the analysis of financial ratios, but it may be influenced to a significant extent by the industry environment, industry risks and factors such as market position of the issuer.

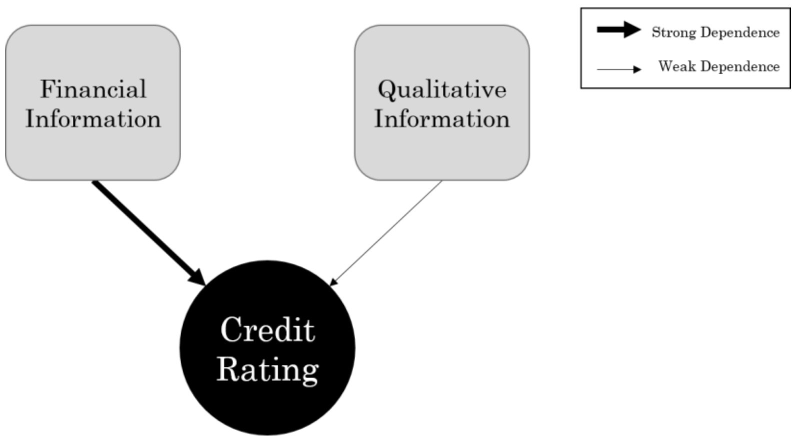

Figure 1.4 Relevance of the two source of information of a credit rating

[21] Associazione Bancaria Italiana (ABI) is the trade association of Italian banks

Quantitative Analysis

This is the most important analysis since it gives an objective vision of the creditworthiness of a company. The focus is on the ability of the company to generate cash. Analysts considers a wide range of financial ratios in the credit rating process and, also, past trends and future developments play a major role. Profitability ratios are fundamental since generating profit is a is a major factor in determining the degree of credit protection and level of credit risk for investors. A company with high margins and return on capital is more likely to generate capital internally and to gain access to external capital sources. Although there tends to be a close connection between cash flow and profitability, it is important to bear in mind that any payment of interest is not made from earnings, which may be subject to a specific accounting treatment. Payments must be made from cash flow. Only if the operating cash flow is sustainable the company is in a position to both service the debt and fund its operations and growth. Thus, the cash flow analysis is fundamental in the credit rating process. The capital structure is another aspect that analysts consider. A company has a higher credit risk if it deeply relies on external source of capital since it is already expose to banks. Thus, a hypothetical new loan will be issued with a higher interest rate. On the other hand, if a company finance its operation with internal funds, it will easily meet its debt obligation and, so, it is perceived as safer. Another important aspect in defining the credit rating of a company is assessing its financial flexibility. In particular, it concerns how a company will meet its debt obligations during spells of volatility and what ways of funding are available to the firm. The more funding options a company has, the higher its financial flexibility.

Qualitative Analysis

As already mentioned, even if the credit rating mostly depends on financial indicators, it is important also to consider the environment in which the company operates. Outside factors can influence the success of a company and, so, its credit rating. Thus, analyst assess the credit rating of a company considering its industry risk. As credit ratings measures the ability of a company to repay its debt obligation, several factors need to be analyzed: for example, the nature of the business cycle and specifically factors such as the cyclicality or volatility of the business. In addition, the general state of the industry or the level of competitiveness and capital intensity also influence the creditworthiness of a company since they impact on its cash flow and, so, on its ability to meet obligations in time. Rating agencies and banks consider the business and financial risk of a company within the boundaries of the industry in which it operates. This is the reason why companies with similar financial ratios may have different values in credit rating. In addition, the market position may be another critical issue for companies operating in a highly competitive industry. Significant factors are: market share, competitiveness, diversification in terms of products and key customers and the ability to maintain or dictate prices in the market. Furthermore, management skills need to be investigated since they influence the risk attitude of the company. The analysts study the long-term future strategic development of the company through the ability of the management. Risk attitude and the company's performance in response to unexpected events are also part of the evaluation of management skills. In the end, the management assessment (And so credit rating) is also influenced by corporate governance.

1.5 Credit Scoring Model

Due to the 2007 financial crisis, the number of defaulted companies has increased worldwide. Thus, it is important to identify accurate tools that can be used by banks and other financial institutions to evaluate the credit rating of a third part. In the previous chapter, the focus was on what kind of information are commonly used by banks or by credit rating agencies when assessing companies' credit rating. This chapter will present the models that are used to translate quantitative and qualitative information in the credit rating. A reliable credit rating model corresponds to a more precise prediction of the default probability of a company. Thus, the results would be the creation of a more trustworthy system either for banks and companies. The Oesterreichische Nationalbank[22] in 2004 identified different "architecture" that banks can used to generate ratings:

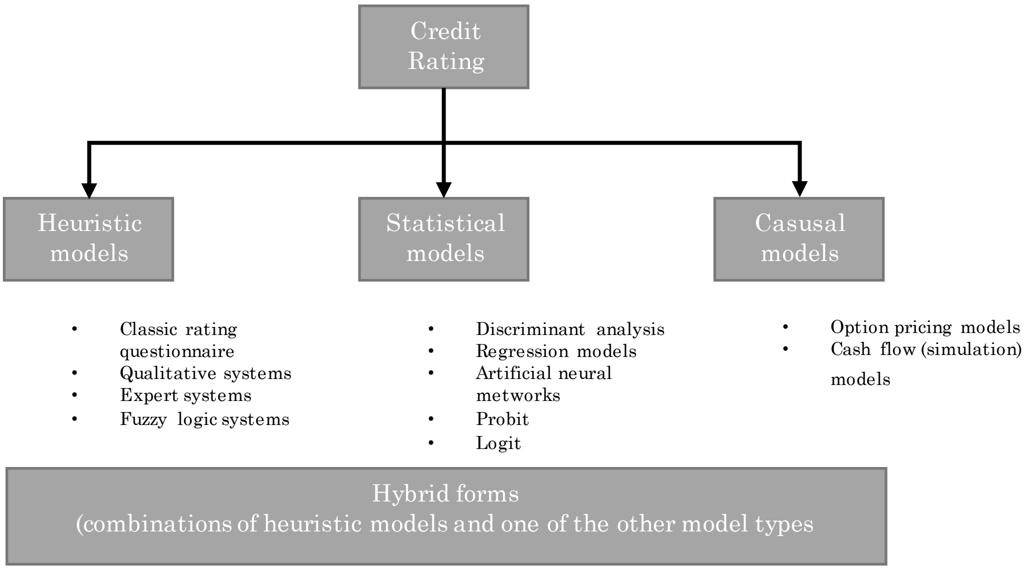

Figure 1.5 Different methodologies to create a credit rating model

This presentation is not meant to describe all the credit rating models. Thus, in this research only the statistical models will be further discussed. This choice has been made to keep the attention of the models that have been effectively considered in the following chapters.

1.5.1 Statistical Models

Since the beginning of the 20th century, a lot of studies regarding the balance sheet have been made with the objective of measuring the economic and the financial performances of companies. However, even if the balance sheet is a proper tool to understand the company's financial position at a point of time, it is not appropriate to use it in order to forecast future economic and financial performances of the company. The balance sheet can provide such information only after some stages of analysis. If used alone, the balance sheet is not able to

[22] The Oesterreichische Nationalbank (OeNB) is the central bank of the Republic of Austria and, as such, an integral part of both the European System of Central Banks (ESCB) and the Eurozone.

describe the complexity of the business situations. To overcome this limit, scholar started to make statistical analysis to assess companies' creditworthiness. This kind of analysis have been called *Credit Scoring* models. They involve the combination of quantitative, such as financial indicators, and qualitative information, such as elements that can be useful to assess the company's creditworthiness. Altman[23] specified that it is important not to underestimate the importance of qualitative measures since they *"can provide as much as 30-50% of the explanatory power of the scoring model"*. The 97% of banks use credit scoring models to assess the creditworthiness of their credit card customers, this percentage fell to 70% when assessing the credit risk of loan customers (Mester, 1997). Afterwards some model of credit risk assessment and financial distress prediction will be analyzed.

1.5.2 The univariate approach

Financial ratios are very powerful in detecting companies operating in financial difficulties. Before the development of quantitative analysis to assess companies' creditworthiness, some agencies provided a qualitative type of information. For example, this was the way through which Dun & Bradstreet[24] provided independent credit investigation in 1849. Essentially, in order to assess the creditworthiness of a company, banks used some basical information, such as borrower character (reputation), capital (leverage), capacity (volatility of earnings) and collateral, the so-called *"4 Cs of credit"* (Altman, 1998).

[23] Edward I. Altman (born 1941) is a Professor of Finance at New York University's Stern School of Business. He is best known for the development of the Altman Z-score for predicting bankruptcy which he published in 1968. Professor Altman is a leading academic on the High-Yield and Distressed Debt markets and is the pioneer in the building of models for credit risk management and bankruptcy prediction.

[24] Dun & Bradstreet, Inc. is an American business services company that provides commercial data to businesses on credit history, business-to-business sales and marketing, counterparty risk exposure, supply chain management, lead scoring and social identity matching.

William H. Beaver[25] is one of the first scholars that created a model to predict companies' default in his work "Financial ratios as predictors of failure". In particular, he considered a sample of 158 of failed and non-failed firms and he identifies a number of indicators able to discriminate between these two groups. In the end, Beaver stated that the ratio between Cash Flow and Total Debt was the most powerful indicator to predict companies' creditworthiness. He obtained a correct classification in the 87% of cases in the year before the default; this percentage decreased to 78% when considering five years before the default. However, even if the prediction power of his model felt down going backward over the years, his univariate approach has set the stage for the subsequent multivariate models.

1.5.3 The Multivariate Approach

The second typology of approach to forecast the credit risk of a company is the multivariate approach. There are at least four methodological approaches to developing multivariate credit-scoring systems: the linear regression, the logit model, the probit model, and the discriminant analysis model (Altman and Saunders,1998). This approach is based on the combined estimation of different variables in order to synthetically evaluate companies' creditworthiness. It gives a complete vision of the company examining different perspectives: the profitability, the financial structure, the liquidity and so on. The multivariate approach is not aimed to concentrate all the different indicators in a single information, but the real objective is to coordinate the trade-offs that are presents in the different parts of the company (Bassi, 2008). For example, one could face the problem of assessing the creditworthiness of two companies: one in better in terms of profitability and the other in terms of liquidity. The problem is to evaluate which one is preferable. The multivariate approach can give a solution; in fact, it creates a unique measure that takes into account the specific trade-off between profitability and liquidity, and that assesses which one is superior to the

[25] William H. Beaver is widely recognized for his innovative research on how accounting information in corporate financial statements affects security prices. He was among the first to investigate financial ratios as predictors of business failure.

other. The crucial point is to understand how the weights of the different indicators are evaluated. In the following pages, the most famous credit scoring model will be analyzed

The Z-Score (Altman, 1968)

In 1968 Altman published most famous discriminant model for predicting bankruptcy called "the Z-score". The initial sample is composed of 66 manufacturing listed US companies: half defaulted and half non-defaulted. The defaulted firms have been selected from all the companies that filed a bankruptcy petition under Chapter X of the National Bankruptcy Act from 1946 through 1965. After the sample selection, Altman collects a list of twenty-two variables divided in five categories: liquidity, profitability, leverage, solvency, and activity ratios. From this list, only five variables were selected *"as doing the best overall job together in the prediction of corporate bankruptcy"* (Altman, 1968).

Thus, the final discriminant function of Altman is as follows:

$$Z = .012\, X_1 + .014\, X_2 + .033\, X_3 + .006\, X_4 + .999\, X_5$$

Where:

- $X_1 = \frac{Working\ capital}{Total\ assets}$
- $X_2 = \frac{Retained\ earnings}{Total\ assets}$
- $X_3 = \frac{Earnings\ before\ interests\ and\ taxes}{Total\ assets}$
- $X_4 = \frac{Market\ value\ equity}{Book\ value\ of\ total\ debt}$
- $X_5 = \frac{Sales}{Total\ assets}$

Altman's model is extremely accurate in classifying 95 per cent of the total sample correctly in the year of manifestation of defaults. The Type I error proved to be only 6 per cent, while the Type II error was even better at 3 per cent.

The discriminant analysis of Altman associates for each company a rating that describes its creditworthiness. In particular, Altman identifies three possible outcomes; a company can have: high, medium or low default risk. During years, Altman revised its discriminant model to adapt it to different economic environments.

Z'-Score (Altman, 1993)

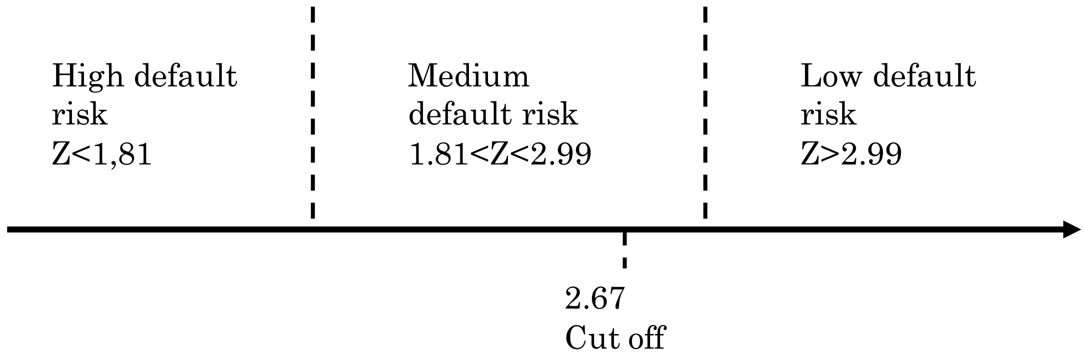

Figure 1.6 The different outcomes of the Z'-Score

In 1993 Altman revised its previous version of the Z-Score model in order to extend it also to non-listed companies. The equation became as follow:

$$Z' = .717\,X_1 + \;.847\,X_2 + \;3.107\,X_3 + \;.42\,X_4 + \;.998\,X_5$$

Where all the variables remain unchanged respect of the previous version except for X_4. In its calculation, the *market value of equity* was replaced by the *book value of equity*. Respect to the Z-Score, the cut-off point was unvaried, the high default risk area is placed below 1.23, while the low default risk one above 2.90.

Z"-Score (Altman, Hartzell and Peck, 1995)

In order to avoid the previous model would be too industry sensitive, Altman, Hartzell and Peck developed a new credit scoring model in 1995. The biggest innovation of the Z"-Score is the removal of the variable X_5. For the authors, this new model is more accurate than the previous ones and it fits very well even to non-manufacturing companies. The new equation is the following:

$$Z'' = 6.56\,X_1 + \;3.26\,X_2 + \;6.72\,X_3 + \;1.05\,X_4$$

Moreover a different version of the Z"-Score has been developed for companies operating in emerging countries. The equation is almost the same, only a constant value was added.

$$Z'' = 3.25 + \;6.56\,X_1 + \;3.26\,X_2 + \;6.72\,X_3 + \;1.05\,X_4$$

In this model, the high default risk area is placed below 1.10, while the low default risk one above 2.60.

O-Score (Ohlson, 1980)

Ohlson[26] believed that the credit scoring model developed by Altman had too much limitations. Thus, in the late '80 Ohlson became the first user of logit in the context of credit risk assessment. As the discriminant analysis, the logit regression model estimate weights of the independent variables and calculate a score in form of default probability of the company examined. The advantage of this method is that it does not assume multivariate normality and equal covariance matrices as discriminant analysis does. He utilized a sample of 105 defaulted companies and 2058 non-defaulted companies operating between the 1970 and the 1976. Ohlson came up with this equation:

$$O - Score = -1.32 - .407\, X_1 + 6.03\, X_2 - 1.43\, X_3 + .076\, X_4 - 2.37\, X_5 - 1.83\, X_6 + .285\, X_7 - 1.72\, X_8 - .521\, X_9$$

Where:

- $X_1 = \log(Total\ assets)$
- $X_2 = \frac{Total\ liabilities}{Total\ assets}$
- $X_3 = \frac{Working\ capital}{Total\ assets}$
- $X_4 = \frac{Current\ liabilities}{Current\ assets}$
- X_5 is 1 if total liabilities is more than total asset, otherwise is 0.
- $X_6 = \frac{Net\ income}{Total\ assets}$
- $X_7 = \frac{Net\ income + Depreciation\ \&\ Amortisation - Devaluation\ of\ sold\ assets}{Total\ assets}$
- X_8 is 1 if the net income has been negative for the previous two years, otherwise is 0.

[26] The Ohlson O-Score for predicting bankruptcy is a multi-factor financial formula postulated in 1980 by Dr. James Ohlson of the New York University Stern Accounting Department as an alternative to the Altman Z-score for predicting financial distress

- $X_9 = \frac{Net\ income_t - Net\ income_{t-1}}{Net\ income_t + Net\ income_{t-1}}$

The O-Score model is more complex than the Altman's models and it also introduced two dichotomous variables. The model has a power of prediction of 96.12% of the cases and the cut-point is at 0.038.

Zmijewski, 1984

Zmijewski[27] developed a different credit scoring model using the probit model. He analyzed listed US companies operating the financial industry in the period between 1972 and 1978. The equation is the following:

$$Zmijewski\ = -4.336 - 4.531\,X_1 + 5.679\,X_2 + .004\,X_3$$

Where:

- $X_1 = \frac{Net\ income}{Total\ assets}$
- $X_2 = \frac{Total\ liabilities}{Total\ assets}$
- $X_3 = \frac{Current\ liabilities}{Current\ assets}$

Zmijewski created a sample of 40 defaulted companies and 800 non-defaulted ones. The model has a power of prediction of 99% of the cases and the cut-point is at 0.50. The biggest critic moved towards this model is to the scarce number of independent variables considered and to the high level of multicollinearity[28] between them.

1.6 Modeling techniques vs New sources of information

In the following section, a deep overview of the main credit scoring models has been introduced. Since the earliest contributions in this field, the literature

[27] Krzysztof Henryk Żmijewski was a polish engineer, professor of Warsaw University of Technology, academic lecturer, former deputy minister of construction, columnist, social worker.

[28] In statistics, multicollinearity is a phenomenon in which two or more predictor variables in a multiple regression model are highly correlated, meaning that one can be linearly predicted from the others with a substantial degree of accuracy.

has pointed major attention on the improvement of performances of credit scoring models. As already presented previously, several studies have been carried out in order to improve accuracy and reliability of default prediction models. This is a natural and obvious results, given the importance and relevance of default.

An original perspective on this topic has been provided by Fernandes (2015). As shown in the following figure, credit scoring performance curves can be represented based on the Cobb-Douglas production function (Cobb-Douglas, 1928) where, as the investment in a single production factor increases, the marginal gain decreases.

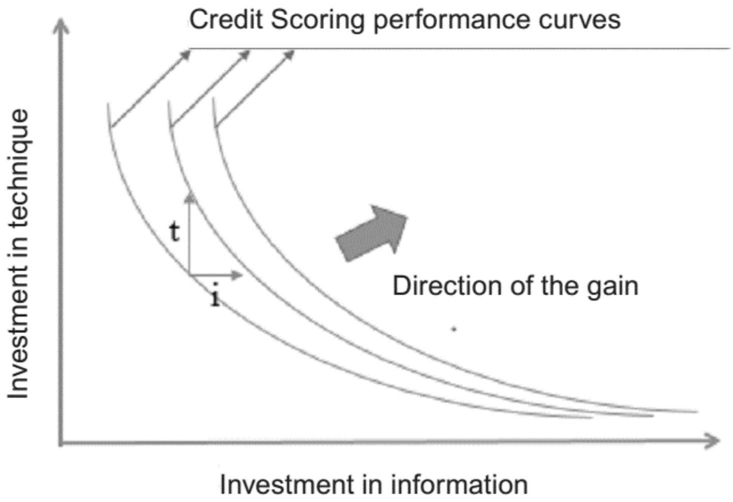

Figure 1.7 Investment in information vs Investments in technique

The main contribution provided by the author is to apply the Cobb-Douglas function to performances of credit scoring models. According to the model suggested by the author, the status of the research in modeling techniques is so advanced that the “leap” to the next performance curves would take higher and higher efforts if academics kept on looking only on modeling techniques. On the other side, investment in information, that means introducing new sources of data within credit models, can lead to higher gain in performances. Consistently with the rise of Big Data, the author conclude that the paradigm should now change: in the future, information variety will become much more important than modeling technique. Thus, technical innovation should mean incorporating new information sources instead of obtaining marginal improvement relying on the same traditional data. The present work belongs to this new paradigm, and the following section aims to provide a review of the state-of-art data currently used in credit scoring models. The following chapters will investigate the possibility of integrating vendor rating data as a new source of information to improve credit scoring models.

1.7 Research Gap

In this chapter, companies' creditworthiness has been assessed only in a financial perspective. In particular, financial ratios are considered the powerful source of information to predict the credit risk of a company and macroeconomic considerations are just background analysis. As the following chapters will highlight, this approach is inadequate since it gives only a partial vision of the company's entire situation (Su and Lu, 2015). Thus, it is misleading to consider financial rating as a way to depict the real picture of companies' creditworthiness. Moreover, the worldwide credit crisis of 2007 has thrust credit rating agencies into the spotlight underling their limits. Policymakers have undertaken a number of initiatives intended to address perceived problems with such ratings: enhancing competition, promoting transparency, reducing conflicts of interest, and reducing ratings-dependent regulation. This has been made in order to overcome credit rating agencies' limits and to avoid another liquidity trap, as the one the world lived in 2007. Therefore, new models to assess the credit risk of a company are arising. The key issue is overcoming the dependence to the only-financial perspective. As this work will highlight, supply chain finance may provide the right tools for creating a more accurate and powerful credit rating. A better credit risk assessment corresponds, on one hand, to an easier access to the debt market for companies and, on the other hand, to a reduction of the risk that banks face lending money. Thus, the final aim of this research is to develop a rating model framework that will include different perspectives of a single company: from the financial to the supply-chain one.

CHAPTER 2 - VENDOR RATING

Nowadays, it is common to claim that the granularity of the competition has moved from the individual company to the entire network of suppliers and customers, called the *supply chain*. The word "*Supply Chain"* (SC) has become a widespread and popular buzzword inside most of the companies across the world.

Furthermore, the recent financial crisis and the subsequent uncertain economic stability posed great attention on identification and mitigation of supply risk within companies. Among many different risk sources, academic literature considers supplier's default risk as potentially disruptive for both buyers downstream and suppliers upstream.

This chapter is structured as follows: first, a brief introduction of Supply Chain Risk and Vulnerability is presented; second, the relevance of supplier's default is discussed providing the example of two impacts that this risk source has on supply chains dynamics; third, the supplier selection and evaluation process is introduced, focusing both on the process as a whole and zooming in the state-of-the-art vendor rating criteria. The chapter concludes with a discussion on the topic of knowledge generated in vendor rating as buyers collect data about suppliers' performances systematically. In particular, the issue of the role that these data could have in a hypothetical is presented.

2.1 Supply Chain Risk and Vulnerability

According to Manuj and Mentzer (2008), a trade-off exists within modern global SCs. On one side, global supply chains allow companies to gain a significant competitive advantage because they can have access to either lower raw material acquisition costs or better quality, open to larger markets and easier access to financing opportunities. On the other side, these opportunities come with a downside: the higher the stakes, the higher the *risk* that companies have to cope with. Millet et al (1990), argue that there is still confusion on the definition of Supply Chain Risk (SCR) and so one of the outcome of their study was providing the following definition: *"Global supply chain risk management is the identification and evaluation of risks and consequent losses in the global supply chain, and implementation of appropriate strategies through a coordinated approach among supply chain members with the objective of reducing one or more of the following – losses, probability, speed of event, speed of losses, the time for detection of the events, frequency, or exposure – for supply chain outcomes that in turn lead to close matching of actual cost savings and profitability with those desired"* (Manuj, Mentzer 2008).

In academic literature, it is common the following classification of Supply Chain Risks into four categories (Christopher and Peck, 2004; Manuj and Mentzer 2008). *Supply* risk represents uncertainty related to inbound supply that might affect the capacity of the company to meet customer demand and expectations, and it is also the focus of the present study. *Demand* risk is about dealing with unpredictable changes in customer's demand profile. *Operational* risk covers those adverse events that could prevent the focal company to successfully fulfil its obligation towards customers and deliver quality products on-time. Finally, *Security* risk relates with unexpected adverse events that might endanger human resources and operations integrity. Since the focus of this study is the supplier's default risk, the rest of the dissertation will cover only the *Supply* risk category.

Supply Chain disruption is defined as any uncalled and unpredictable event that lead to Supply Chain risk (Wagner and Bode, 2006). Any disruptive event can be classified according to its probability of occurrence and severity. They argue that Supply Chain disruption is not enough to obtain the final impact on SC. In fact, another dimensions must be considered, the Supply Chain vulnerability. The same Supply Chain disruption may lead to completely different results, depending on the extent to which every SC is designed to resist and recover from the adverse event (Blaikie et al, 1994). Another author, Svensson (2004), distinguish between *atomistic vulnerability*, that take place in a single part of the Supply Chain, and *holistic vulnerability*, that consider the entire Supply Chain. A strong hypothesis built by Wagner and Bode (2006) is that supply chain design characteristics drive the supply chain vulnerability which is, thus, an intrinsic characteristic of the SC. We borrow this concept from them and follow this direction in the present work, focusing only on the *atomistic vulnerability area*, in which Supply Chain Risk is analyzed at the individual firm level.

There are many publication in literature that have tried to investigate drivers of Supply Chain Vulnerability. This means that academics have tried to identify which characteristics of SC influence SCV and to what extent. In the following table are summed up most relevant drivers for supply-side risk of SCV with the academic sources.

DRIVERS	**SOURCE**
Supplier dependence	Giunipero and Eltantawy, 2004; Hendricks and Singhal, 2005a; Ju¨ttner, 2005; Spekman and Davis, 2004; Svensson, 2004a
Supplier concentration	Norrman and Jansson, 2004; Tang, 2006a; Zsidisin et al., 2000
Single sourcing	Hendricks and Singhal, 2005a; Zsidisin et al.,2004
Global sourcing	Ju¨ttner, 2005; Kraljic, 1983; Peck, 2005, 2006; Seshadri and Subrahmanyam, 2005

Table 2.1 Academic source on Supply Chain reviewed in the present research

Hallikas et al (2005) have defined *supplier dependence* as "the extent to which an organization sources inputs from a supplier for which there are few alternative sources". This leads to a higher bargaining power in the hands of the suppliers because it would be more complicated for the buyer to substitute the supplier in case of supply-side disruption. The strength of this driver is reinforced as both the importance of the supplied item and the complexity of the supply market increase (Giunipero and Eltantawy, 2004). *Supplier concentration* is the situation when there is an unbalance between the number of suppliers and buyer in the same supply market. A high concentration of suppliers is consistent with the present trend of companies reducing its supply-base establishing strategic long-term relationships, but it has a negative effect on SCV (Cavinato, 2004; Choi and Krause, 2006). Wagner and Bode (2006) argue that single sourcing is the extreme case of supplier concentration. Companies become unable to switch supplier in case of supplier disruption. *Global sourcing* has a clear impact on raising uncertainty inside SC. In fact, having the supply base spread all over the world can create competitive advantages by providing access to cheaper acquiring costs and higher quality, but at the same time, global sourcing increase complexity and uncertainty across the SC (Goetschalckx et al, 2002).

As stated before, Supply Chain Risk Management has gained great attention by academic researchers over the last years. The higher frequency and intensity of unpredictable events has heightened the regard towards this topic (Wagner and Bode, 2006). A wide number of academic (Coleman, 2006; Helferich 2002; Munich Re, 2006) focused mainly on exogenous "macro" disaster such as terroristic attacks or natural catastrophes. Other authors wanted to investigate deeply cases where the Supply Chain disruption stemmed from an internal source (Latour, 2001; Norman and Jansson, 2004; Sheffi 2005). For the purpose of this study, we are more interested in these latter works since a supplier's bankrupt is, by definition, an internal cause that could trigger SC disruption. According to Hendricks and Singhal (2005), they have demonstrated empirically that such events have a strong negative impact on both shareholders' value and operative performance. Nevertheless, current Supply Chains do not seem to be prepared to take the step forward a more robust and resilient configuration. Instead, Christopher and Lee (2004) argue that "*the vulnerability of supply chain to disturbance or disruption has increased*". Other researchers (Christopher and Peck, 2004; Harland et al., 2003; Hendricks and Singhal, 2005; Tang, 2006) explain this trend referring to the increased pressure on competition and the growing complexity worldwide due to the already mentioned three macro trends (outsourcing, globalization and e-commerce). Consequently, many studies have been conducted to provide guidelines with the ultimate goal of creating resilient, robust and secure Supply Chain (Chopra and Sodhi, 2004; Lee and Wolfe, 2003; Martha and Subbakrishna, 2002). However, their works has more a normative nature than an actual practical implication. Wagner and Bode (2006) state that the relationship between Supply Chain design and Supply Chain Risk exposure deserves deeper investigation. They underscore the dependence between supply chain design decisions and exposure to risk. In conclusion, we might claim that purchasers' main task is to ensure SC operativity coping with growing globalization and outsourcing. Risk mitigation must be also cost-effective and this generates a trade-off in purchasing decisions.

After having provided some conceptual definitions, it is useful to discuss about risk sources and illustrate different classification produced in academic research during past years. The variety of Supply Chain Disruptions imply a wide heterogeneity of Supply Chain Risk Sources (SCRS) defined as root-causes of the adverse events. A common classification of SCRS divide them into three macro categories, according with their nature: D*emand-side risk, Supply-side risk* and *Catastrophic*.

According to Juttner (2005), *Demand-side risk* relates with SC disruption that come from downstream actor of the SC. These kinds of unpredictable events could stem from any of the actors operating downstream in the SC. Some academic works have focused on disruptions triggered by failures in the distribution network (McKinnon, 2006), others analyzed risk associated with unforeseeable end customers' variation in demand (Nagurney et al., 2005). Major consequences of demand-side risk are goods shortage by end-customer (stock-out cost) or overstocking (obsolescence costs) (Lee et al, 1997).

Catastrophic risk includes a vast kind of disruption that usually take place seldom and with a massive and extensive impact. They range from natural hazard to socio-economic crisis. Negative effects on SC are evident since production facilities and distribution networks are susceptible to such adverse events. Terrorisms as well is a threat that more and more SC should be aware of (Sheffi, 2005).

Supply-side risk relates with the inbound flow of materials, human resources and funds to ensure the correct fulfilment of operations. One of the earliest works was produced by Kraljic (1983) that introduced the idea that companies should actively manage suppliers' risk and measure their exposure to possible supply-side disruption. Supply-side risk relies in supplier business risk, production capacity problem, quality issues (Zsidisin et al, 2000).

2.2 Impact of supplier's default on Supply Chains

Once Supply Chain Risk has been defined and classified, it is possible to focus on the Risk Source of interest, that is supplier's default, and take a step forward in the analysis. For this reason, the rest of the dissertation will deal only on the supplier's default. A literature review of already existent publication on this topic is carried out in order to have an estimation of the magnitude of this disruptive event and evaluate the relevance of this research. First, the "domino" effect due to a supplier's default is presented. Second, the perspective of supplier portfolio management is taken and implications of risk on sourcing decisions are briefly introduced. The aim of this section is to show the relevance of the supplier's default problem and give the "feel" of the impact that such issue has on companies' bottom line. At the end of the section, the reader should have a better comprehension and feeling that efforts to improve default prediction models must become a priority in research.

2.2.1 Contagious effect: Supplier's Default correlation

The purpose of this paragraph is to investigate on a significant effect of supplier default in Supply Chain: the correlation of default in time. Zhou (2001) defines the existence of correlation when "*the likelihood of one company's default is affected by the default of other companies*".

According to the Supply Chain perspective mentioned in the beginning of the chapter, firms are more and more inter-connected. The growing trend of outsourcing and focusing only on core business has multiplied the number of relationships that a firm must manage to properly run its operations. Furthermore, companies, more and more often, rationally manage their supplier portfolio, according with suppliers' relevance to company's results. At the same time, the number of strategic partnerships raised constantly over the last years. A strategic partnership is characterized by: a long-term time horizon in order to make the investment return and be profitable; a relevant specific relationship investment. It consists in investments that a partner make, that has value only inside the relationship and not outside. In other words, the higher the specific relationship investment, the higher the risk associated with the relationship.

Another important contribution has been provided by Babich et al. (2007). They have demonstrated, through a Stackelberg game model in which there are multiple suppliers and only one buyer, that is of utmost importance that the buyer's decision making include joint (correlated) supplier default distribution because it affect buyer's profit.

There is a plethora of studies and model on this topic that suggests default correlation relevance in the study field of risk management of portfolio in corporate banking. In fact, understanding default correlation through accurate models would allow bank and other financial institution to better plan and manage their capital requirement and face strict regulation on the matter (Gordy, 2003).

A group of studies wanted to shed light on positive correlation between suppliers' default. Among many different drivers explored, the literature has focused around some main points.

First, correlated defaults happen because firms are *exposed to the same risk factors* or to same changes in the context. This causes correlated changes in conditional default probabilities (Das et al, 2007). One of their major findings is that systematic time-variation in default risk is driven more by macro-economic variability, rather than variation in individual debt levels. Companies experiences changes in macro-economic variable that affect every company across the sector. In other words, companies might go bankrupt in the same period because they experience the same stress change in the market and they feel the same effect on their business. One example of these macro-economic factor has been discussed by the earliest works on this topic by Duffee (1998) and Keenan (2000). They found that default rates are significantly correlated to the default-free interest rate.

Second, a supplier's default may induce to other firms' default. This means that defaults could be *contagious* and could affect others companies inside the same SC. As it happens in financial crisis, a sudden large rating downgrade of a company can provoke simultaneous response from the market (Giesecke, 2004).

Finally, *learning from default* could be further source of correlation. In fact, Das et al. (2007) argue that a company that disclose its accounting irregularities could trigger other firms to understand that they are in the same situation. The latter reason is the most likely to take place also between different Supply Chains.

Furthermore, another root cause of default correlation has been traced back to analogies between decisions taken by suppliers of the same buyer. In detail, it has been observed in literature that suppliers often keep horizontal cross relationships with other suppliers of the same buyer (Choi et al., 2002; Wu and Choi, 2005). Wu and Choi (2005) argue that it is not uncommon that suppliers that share same buyer, can work together, and making comparable decisions on operative issues. Obvious consequence of decision taken in the same direction is that if one supplier experience financial distress due to wrong decision, it is likely that also the other supplier would suffer as well. This is one of the possible explanation of default correlation in some industries.

The review of the aforementioned academic publications, stresses further the relevance of our research. Furthermore, this brief overview of main default correlation drivers aimed to introduce the reader to the concept of contagious default. The takeaway from this paragraph is that default correlation represents a consolidated and wide-spread phenomenon that increase the importance of improving existent default predictive model in order to minimize the risk of SC disruption in the future.

2.2.2 Multi-sourcing strategy

This paragraph aims to provide some insights about the potential implications that a supplier's default has on buyer's strategic sourcing decisions. In fact, in dealing with growing complexity and risk exposure of global supply chains, a significant contribution is provided by choosing the right purchasing strategies (Porter, 1985).

In literature on sourcing strategy, it is common to find evidence that multi-sourcing is the best strategy to mitigate supply-side risk. This consists in diversifying the supply base and/or create redundant capacity (Anupindi and Akella, 1993; Horowitz, 1986; Tang, 2006). However, this choice has a major downside: multi-sourcing entails higher costs for the purchasing organization. In fact, managing a wider supply-base means a proliferation of orders, calls, data and effort to maintain relationships. Especially with the growing trend of setting up more and more strategic partnerships, multi-sourcing strategy becomes less cost-efficient and unbearable pursue. Luzzini et al (2014) state that reducing the supply base leads to several benefits, among them: i) increase effectiveness of supplier selection process thanks to the higher time available to allocate to each supplier; ii) gain cost advantages by aggregating purchased volume in fewer suppliers.

To sum up, purchasing strategy is moving towards a reduction of the supply-base and a development of more and more strategic and long-term partnerships, but companies prefer to pursue supply-risk mitigation by taking expensive multi-sourcing decisions. This perspective provides further evidence that avoid supplier disruption due to supplier's default is a major problem for purchasing organization that lead to sub-optimal decision to mitigate risk. There is clear indicator that more effort should be focused around avoid supplier's default, helping companies reaching optimal solutions, reducing the likelihood of risk source. By the end of this section, the Reader should have a more complete idea of the importance of study further the phenomenon of supplier's default. In particular, analyzing and improving existing predictive default models would reduce the risk exposure and costs of purchasing companies.

2.3 Supplier evaluation and selection process

In the previous sections, the growing relevance of supplier's default risk source has been introduced. Even though the root cause of a supplier's default could be traced back to many different sources, it is common view that a major contribution in avoiding supplier's default is the proper management of supplier evaluation, selection and monitoring process.

The role itself of the purchasing function has changed dramatically over time. In the past, the strategic contribution of purchasing was not recognized but, from Lewis (1943) on, more and more researchers pointed out the overall strategic importance of purchasing. In the automotive and high-tech industry, purchased items account for up to 80% of the total production cost (Weber et al, 1991) and Globalization of sourcing and e-commerce advent has widened a purchaser's choice set and literature has provided professionals with a broad range of supplier selection models supporting the vendor selection complexity (De Boer et al, 2000). The goal of such models is twofold: improving both effectiveness (focus on the right problem, choosing suitable critera, etc.) and efficiency of purchasing decisions (automation and faster storage of purchasing decisions, elimination of redundant criteria, etc.) (De Boer et al., 200).

Over the last years, many studies have been investigated changes in relationships between suppliers and buyers. As outsourcing gains relevance across every industry, also the process of supplier evaluation and selection does the same (Yan et al, 2003; Choy et al., 2003). Several authors have stressed the attention on the win-win cooperative relationships and how suppliers are crucial in driving buyer's economical results with its performance (Cooper and Ellram, 1993; Han et al, 1993; Van den Bulte, 1994). In other words, many researchers consider the role of supplier as crucial for reaching superior business performances (Choi and Hartley, 1996; Flynn et al., 1994; Vonderembse and Tracey, 1999). Furthermore, many researchers (Kraljic, 1983; Jackson, 1983; Shet, 1973; Hahn et al., 1983; Ansari and Modaress, 1980; Treleven, 1987) have theoretically emphasized the strategic relevance of the supplier selection process, highlighting the trade-off among quality, cost and delivery performance. A supplier selection and evaluation process that is run effectively and is aligned with corporate strategy is a powerful instrument in the hands of companies. Huang and Kesar (2007), argue that the technological development has led academics on focus mainly on quantitative optimization of models, losing the connection with strategic business objectives. They claim that, in today's world evolving so rapidly, it is impossible to create an exhaustive set of metrics to select suppliers. Instead, they stress the importance of a robust set of configurable metrics based on corporate strategic goals. Benefits are numerous: Janker (2006) explains how there is the possibility, thanks to a careful supplier selection, to minimize inbound control inspection on goods, because of the high service quality provided by the supplier. This would help companies to incur in lower control costs. Furthermore, Hartmann et al. (1992) shows that suppliers that work efficiently have higher chances to obtain an extension of the contract. He demonstrated that this would help the relationship between buyer and supplier to enter a virtuous circle that would improve performances for both sides.

Most professionals would agree that no one best-way of approaching supplier evaluation and selection is present. However, it is commonly settled that main objective of the evaluation process is minimize supply risk while maximize value for the purchaser (Handfield, 2008 book). Hartmann et al. (1992) was one of the first to state that goals of suppliers' evaluation are the optimization of procurement costs and guarantee safety of supply.

The foundation of an effective supplier selection process is a solid supplier evaluation methodology. Traditionally, price has been the only relevant factor in evaluating and selecting suppliers, but as Gunasekaran et al (2001) argue, competitive priorities have changed over time and other factors as quality, delivery and flexibility has become increasingly important.

Before entering into details of which are the main attributes, or criteria, used for supplier evaluation, it is worth to take a process view to understand how the supplier evaluation and selection process is articulated and how it fits into corporate strategy. Chen (2010) claims that supplier selection and evaluation process must be designed based on the supply integration process which link to corporate strategy. In fact, decisions about requirements and evaluation criteria are influenced by the degree of integration that the buyer wants to achieve with the supplier.

According to the growing complexity of the purchasing process, since the earliest works, there is evidence in literature that some factors, that are characteristics of supplied-object and the supply-market, can heavily influence the purchasing process. In other words, depending on the nature of the purchase, a different amount of resources, criteria and models would be used to make the decision. This is a perspective that many authors have studied since the earliest contributions on the topic were published.

For instance, the seminal work by Faris (1967), firstly introduced the problem of distinguishing between different purchasing situations, according to the degree of purchasing complexity. He identified three different cases: i) *new task situation*, ii) *modified rebuy* and iii) *straight rebuy*; with a descendent level of complexity. Another work by Kraljic (1983) became soon a cornerstone in the strategic supplier portfolio management. He was the first to start differentiating the purchasing process following a bi-dimensional approach: to *i*) *relevance* of the product (i.e. impact on profit) and *ii*) *supply risk,* proxied as "supply-market complexity”. The combination of these two factors creates a 2x2 matrix that classify supplied products into four cells and Kraljic (1983) provides some directions and managerial recommendations for each of them. Following, the purchasing portfolio matrix (Kraljic, 1983) and the classification of purchasing situation (Faris et al, 1967).

Classification of purchasing situations (Faris et al., 1967)

New task situation	Entirely new product/service; no previous experience No (known) suppliers High level of uncertainty with respect to the specification Extensive problem solving; group decision-making
Modified rebuy	New product/service to be purchased from known suppliers Existing (modified) products to be purchased from new suppliers Moderate level of uncertainty with respect to specification Less extensive problem solving
Straight rebuy	Perfect information concerning specification and supplier Involves placing an order within existing contracts and agreements

Purchasing portfolio matrix (Kraljic, 1983)

	Low-supply risk	High-supply risk
Low-profit impact	*Routine items* Many suppliers Rationalise purchasing procedures Systems contracting Automate/delegate	*Bottleneck items* Monopolistic supply market Long-term contracts Develop alternatives (internally) Contingency planning
High-profit impact	*Leverage items* Many suppliers available Competitive bidding Short-term contracts Active sourcing	*Strategic items* Few (difficult to switch) suppliers Medium/long-term contracts Supplier development/ partnership (develop alternatives ‘externally’) Continous review

Table 2.2 Kraljic’s Purchasing portfolio matrix (Source: Weber)

According to De Boer et al. (2000) an intuitive general structure of the process is the following:

1. *Problem formulation*: this phase consists in understanding how the purchase relates with corporate strategy. Tools used to define strategy comprehend SWOT analysis and Porter’s Five Forces model.
2. *Formulation of criteria*: this phase deals with designing the subset of criteria helping purchasers evaluating vendors. This phase link operative decisions with strategic ones. To do so, the definition of main evaluation criteria is carried out by breaking down strategic goal into sub-goals and eventually in precise attributes to be measured (Chen, 2010).
3. *Qualification*: reducing the set of supplier population to a smaller subset of potential suppliers that meet minimum requirements.
4. *Vendor selection*: this step consists in making the final choice about the sourcing.

Some researchers include also the monitoring step in the entire process:

5. *Assessment of supplier performances*: Delphi method is used to create a questionnaire to evaluate supplier performance over time.

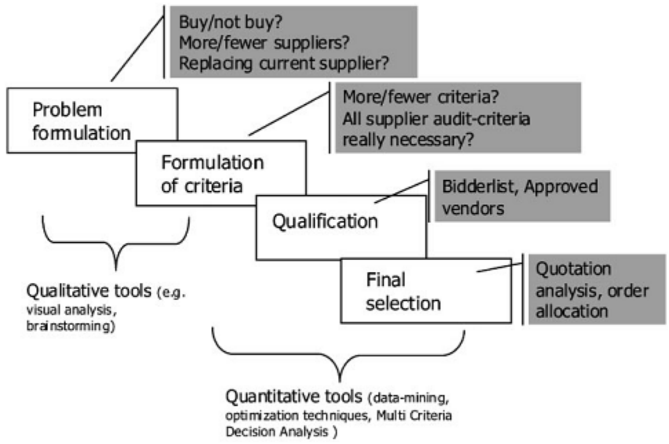

Figure 2.1 Structure of Vendor Selection and Evaluation Process (Source: De Boer 2001)

Following De Boer et al. (2000), different information and tools are used in the different phases of the process. In the figure above, it is highlighted that the "problem setting" side of the problem takes advantage of *qualitative tools* (e.g. visual analysis or brainstorming), while the "decision-making" part exploits *quantitative tools*.

The extensive literature on supplier selection models has been focusing around two main streams: *i) application of multi-variables tools to help decision takers to create synthetic measures out all the different variables in order to rank suppliers and eventually select the best one* (Weber et al., 1991; Kenneth and Thomson, 1990; Timmermann, 1986); *ii*) *identification of criteria to include in the assessment of* suppliers (Dickson, 1966; Narasimhan, 1983; Chow et al., 1993; Weber et al., 1991).

This section is structured in the same way. First, an overview of the supplier evaluation and selection tools used in every step of the process is presented. Second, a discussion about the problem of defining vendor rating criteria follows. After a brief presentation of issues related to this problem, a review of most popular criteria in literature has been performed.

2.3.1 Supplier evaluation and selection tools

Problem formulation & formulation of criteria

As mentioned before, these two phases are characterized by the use of qualitative supporting tools. There is little evidence in literature on structured and formal method on this phases. Some exploratory studies have been provided by Mandal and Deshmukh (1994) and Vokurka et al. (1996).

Qualification tools

Qualification of suppliers consists in "filtering" them in order to reduce the number of potential suppliers, optimizing the resource utilization in the process. In fact, the evaluation of a supplier requires a high utilization of resources (time and money). De Boer et al. (2000) defines this step as "sorting" suppliers, rather than ranking, which is what is performed in the next step.

Categorical methods

This is the simplest qualitative methods available for supplier qualification. It relies only on purchaser's experience and historical data. In fact, the supplier is evaluated on a three-level scale (Bad, Neutral and Good) for several dimensions. Finally, an overall evaluation is assigned to each supplier.

Data envelopment analysis (DEA)

This method has found several application and popularity in literature thanks to its wide applicability and customization. It is based on the concept of *efficiency,* defined with the ratio between input (resources, cost criteria) and output (benefit, outcome). With an adjusting system of weights, the model discriminates between efficient and inefficient suppliers, helping purchasers in narrowing the pool of prospective suppliers. Weber dedicated much effort in studying DEA (Weber, 1992; 1996) also with some relevant negotiating empirical applications (1998). Afterwards, the literature about DEA literally spread in the first decades of 2000s,

Cluster analysis (CA)

Cluster analysis is a model that is widely applicable in several contexts due to its flexibility. In supplier selection models, this means grouping all suppliers into smaller *clusters* according to some scores. By setting some variables as requirements, a classification algorithm create clusters stepwise with the goal of maximizing external variance and minimizing internal variance. This results in having a final set of potential suppliers that are homogeneous, and thus comparable, as per the requirements variables.

Vendor selection tools

Most of the supporting models in this field relates with this phase of the process. In literature, many multi-criteria decision making approaches have been conceived. A first distinction made by De Boer et al. (2000) divides models into two categories, according to the numerousness of the supplied items. Thus, they identify *single-deal* and *multiple-deal*. The authors argue that a buyer could take advantage of *multiple-deal* approach by leveraging on quantity discounts based on overall cross-reference purchased volumes.

According with De Boer et al. (2000), another differentiating factor is the presence (or absence) of inventory management perspective (and costs) in the evaluation of alternative suppliers.

The third, and major, classification suggested by the authors is about the specific technique used.

Simple multi-attribute rating technique (SMART)

This models have the common characteristic that a "score" is given to each supplier, usually calculated as a weighted sum of the scores obtained by a given supplier on every dimension. Weights assigned to criteria represent the relative importance that dimensions have relatively to other dimensions. These models have been widely discussed in literature and, in the last years, adjusted versions of simplest model have been conceived. Weber et al (1991) claim that linear weighting models are, at their time, the most popular models in vendor selection.

In particular, two theories of linear weighting models are present: *i) compensatory models*, where positive and negative performance on different dimension can compensate with each other in the overall rating score; *ii) non-compensatory models*, where performance dimension are kept separated, thus a minimum score in each dimension is required (Grando and Sianesi, 1996).

Another issue that has been widely discussed in literature is the capacity of linear weighting models of dealing with uncertainty and weights affected by inaccurate estimations. Some attempts concerning simulation-based approach (Soukoup, 1987), Analytic Hierarchy Process (AHP) (Narasimhan, 1983; Masella and Rangone, 2000), Analytical Network Process (ANP) (Sarkis and Talluri, 2000) and Fuzzy Sets Theory (FTS) (Morlacchi, 1997) has been carried out.

Other contributes have been provided by Barla (2003) and Huang and Keska (2007).

Total cost of ownership (TCO) models

This group of models aim at estimate every cost involved in the prospective set up of a relationship with the supplier. Purchasing function must quantify every expense that a company incur throughout the whole lifecycle of the supply item. A framework suggested by Ellram (1994) divides costs into i) pre-transaction cost; ii) post-transaction costs.

Mathematical programming models

These models allow the purchaser to clearly define the *objective function* and describe the problem as a maximization (profit) or minimization (costs) of the function itself. Unquestionably, if applied correctly, these models lead the manager to the optimal solution thanks to their robustness and objectivity. However, a potential downside of these models is that they neglect any qualitative variables. In their literature review, Ho et al (2010) identify five types of mathematical programming models: *i) linear programming; ii) integer-linear programming; iii) integer non-linear programming; iv) goal programming; v) multi-objective programming*.

Ho et al. (2010) analyzed 78 articles from 2000 to 2008 and part of their findings are about defining the most popular approach in vendor selection models. As a preliminary hypothesis, they separated models in two categories: i) *individual approach*; *ii) integrated approach*. The former concerns specific techniques applied singularly, as a stand-alone model, while the latter is a combination of two different techniques with the goal of balancing pros and cons of the used methods. In their work, they found that *individual approaches* are still more popular than *integrated* ones.

Furthermore, among the individual approaches, they report that the most popular technique is DEA, thanks to its robustness and adaptability, followed by mathematical programming, AHP, ANP, Fuzzy set theory and SMART. However, DEA has also some drawbacks. Ho et al. (2010) explain that purchaser could get confused with input and output variables; they also argue that DEA is affected by the subjective assignment of ratings to qualitative criteria that could lead to inconsistent results. Finally, they claim that the most "efficient" supplier is not always the most "effective" supplier, thus this last downside of DEA is against its nature.

As far as integrated approaches are concerned, AHP results to be the most suitable method to be integrated with other methods, thanks to its easiness of use and flexibility (Ho, 2008). In fact, thanks to its effective consistency check, AHP could be combined with models that incorporate other sides of the problems (resource limitations, efficiency, etc.). The most popular *integrated* approach is the AHP-GP (Ho, 2010). In this combined approach, AHP was used to determine relative importance of evaluation criteria based on joint decision-making process. Afterwards, weights were incorporated into the GP model that produce the outcome of the selected suppliers and other interesting variables to define the purchase (order quantities, etc.). However, AHP presents also a main downside: it is time-consuming because it needs consensus of the participants to be validated and, if the process does not pass the final consistency test, it must be restarted until it reaches a consistent result.

In this brief literature review of main vendor selection models, the reader should have understood the evolution of vendor selection models in time. In the recent past, academic research has focused on developing models that could deal with the growing uncertainty and complexity of the external environment. An example of this trend is the growing empirical researches of AHP (that provides robustness against uncertainty) and Mathematical Programming (which is strong to cope with complexity due to its flexibility).

Our analysis revealed a large number of different models, ranging from simple to complex. Data Envelopment Analysis (DEA) and AHP result to be the most popular models in literature.

2.3.2 State-of-the-art vendor rating criteria

Purchasers take advantages of vendor rating criteria in different phases of the vendor selection process. In the *qualification/selection* phase, specific attributes are designed to assess potential suppliers, while in the *evaluation* phase, active suppliers are constantly monitored on certain performances. As already mentioned in the previous sections, academic literature has spread around the supplier portfolio management topic. The basic implication is that any vendor selection process must by tailored according to the type of good or service that is exchanged (Luzzini et al, 2015). For this reason, also vendor rating criteria must be selected to respond every time to the supply requirements. Thus, strategic long-term suppliers cannot be evaluated on the same attributes as non-critical short-term suppliers.

Since evaluation criteria must cover a wide range of dimensions (commercial, quality, logistics, etc.), the process of determining the final set of attribute is multi-actor by nature. According to Luzzini et al. (2014), the *definition of KPIs* could be structured in two different ways: i) *shared design*, where all the actors involved take part in the collective definition of the whole set of metrics; ii) *independent design*, where every actor is responsible of designing the KPI of interest. There is also the case where purchasing function is the only supervisor of the KPI definition process (single-actor).

A critical step in the vendor selection process that is collateral to KPI design is the *definition of weight* for attributes. This process could be carried out following two different approaches: i) *shared*, where decisions about weight to assign are collective and consensual; ii) *purchasing-driven*, where only purchasing is involved in this task. According to Luzzini et al. (2014), this is a collaborative step and, thus, *shared* approach is the most suitable.

The identification of the most effective vendor selection criteria has been of major interest in literature since 1940s. In the earliest years of purchasing development, a common practice was to evaluate suppliers based only on a single criterion, typically purchasing cost. As literature flourished on the topic, the perspective on vendor selection criteria becomes wider, since the evaluation on a unique dimension appeared to be too restrictive. Dickson (1966), reviews the already existent literature by stating that there were at least 50 meaningful attributes to consider in the supplier selection problem.

Rank	Factor	Mean rating	Evaluation
1	Quality	3.508	Extreme importance
2	Delivery	3.417	
3	Performance history	2.998	
4	Warranties and claim policies	2.849	
5	Production facilities and capacity	2.775	Considerable importance
6	Price	2.758	
7	Technical capability	2.545	
8	Financial position	2.514	
9	Procedural compliance	2.488	
10	Communication system	2.426	

Table 2.3 Vendor evaluation criteria (Source: Dickson, 1966)

Several years later, Weber and Current (1991) conceived a multi-objectives method for suppliers' selection that would help purchasing manager to evaluate existing trade-off between different vendor performances. In fact, it is hard for any supplier to excel in every performance as a quality-oriented vendor will probably have higher cost than the average (Ben Akiva, 1991; Hagerty, 1986).

The work provided by Weber et al. (1991) represents a cornerstone of the literature review on this topic. They analyzed 74 academic papers with the purpose of ranking the most meaningful vendor selection criteria and compare them with the importance assigned by Dickson in his early study. They found that the majority of reviewed articles discussed the importance of having more than one single criterion in the evaluation of suppliers, demonstrating the multi-objective nature of vendor selection problem. The following table sum up the results of their work, where "top-of-the-list" attributes like *price, quality, delivery on time* and *production facility and capacity* were considered the most important attributes in vendor selection. An interesting interpretation of the figure below is that there are some differences in Dickson importance ranking and the author's ranking. Some attributes that are ranked "top-of-the-list" in the Weber et al.'s charts, were not considered as priorities during Dickson time. This could be read as a further confirmation that the choice of the most meaningful attributes in vendor selection is strongly affected by how changes in business context. It is interesting to notice how price was still the most popular criterion in literature until 1991. This is clearly a legacy of the traditional mindset where purchasing cost was the only attribute used in vendor selection.

Evaluation criteria	Dickson importance ranking	Weber importance	Reference quantity
Price	6	Very important	61
Deliver on time	2	Very important	44
Quality	1	Extremely important	40
Equipment and capability	5	Very important	23
Geographic location	20	Important	16
Technical capability	7	Very important	15
Management and organization	13	Important	10
Industrial reputation	11	Important	8
Financial situation	8	Very important	7
Historical performance	3	Very important	7
Maintenance service	15	Important	7
Service attitude	16	Important	6
Packing ability	18	Important	3
Production control ability	14	Important	3
Training ability	22	Important	2
Procedure legality	9	Very important	2
Employment relations	19	Important	2
Communication system	10	Very important	2
Mutual negotiation	23	Important	2
Previous image	17	Important	2
Business relations	12	Important	1
Previous sales	21	Important	1
Guarantee and compensation	4	Very important	0

Table 2.4 Ranking of Supplier selection criteria (Dickson and Weber)

Other authors (Cardozo and Cagley, 1971; Chapman and Carter, 1990; Dempsey 1978) have carried out empirical studies to focusing on relative importance of quality, delivery, costs. Latest studies illustrate how firms use purchasing cost together with other attributes as quality, flexibility, delivery and services when evaluating vendors (e.g. Hirakubo and Kublin, 1998; Li et al., 2006; Wilson, 1994).

An interesting topic on criteria selection is the relative weight that each purchaser assigns to different criteria. On this purpose, in their study, Verma and Pullaan (1998), wanted to investigate the difference between *perceived trade-off*, that is the explicit and theoretical relative importance of performance, and *actual trade-off,* that is the relative importance that it is possible to see realized in managers' decisions. In their empirical study, they found that managers perceive quality to be the most relevant attribute to evaluate a supplier, but, looking at their actual decisions, they gave more importance to other criteria like delivery and costs.

Gunasekaran et al (2001) create SCM metrics framework classifying them into SCOR phases (*Plan, Source, Make, Deliver*). Their first research (Gunasekaran et al., 2001) focuses on the definition of a set of measures that cover all the aspect of SCM. They provided purchasers with a *toolkit* of metrics divided by two different dimensions: i) *decisional level* (operational, tactical and strategic) and ii) *nature* (financial vs non-financial). In their second research (Gunasekaran et al., 2004), they performed an empirical analysis, using a survey, starting from the whole set of metrics from their previous research, trying to understand which ones are more relevant in assessing SC performances. The result of their empirical analysis is reported in the following table where, in every cell, metrics are reported descending by importance.

As already mentioned in the previous section, Ho et al. (2010) reviewed several articles. The aim of their work is twofold. In fact, on one hand, they want to understand which are both the most popular vendor selection models, while on the other hand, some insights about the most popular vendor evaluation criteria are reported. Quality is found to be the most popular criterion, followed by "delivery, price, manufacturing capability, service, management, technology research and development, finance, flexibility, reputation, relationship, risk and safety" (Ho et al. 2010). It is important to remark that, behind each criterion name, there are many attributes that slightly differ from each other. For instance, "acceptable parts per million" and "net rejections" are both in the "quality" field.

Supply chain activity/ process	Strategic	Tactical	Operational
Plan	Level of customer perceived value of product, Variances against budget, Order lead time, Information processing cost, Net profit Vs productivity ratio, Total cycle time, Total cash flow time, Product development cycle time	Customer query time, Product development cycle time, Accuracy of forecasting techniques, Planning process cycle time, Order entry methods, Human resource productivity	Order entry methods, Human resource productivity
Source		Supplier delivery performance, supplier leadtime against industry norm, supplier pricing against market, Efficiency of purchase order cycle time, Efficiency of cash flow method, Supplier booking in procedures	Efficiency of purchase order cycle time, Supplier pricing against market
Make/ Assemble	Range of products and services	Percentage of defects, Cost per operation hour, Capacity utilization, Utilization of economic order quantity	Percentage of Defects, Cost per operation hour, Human resource productivity index
Deliver	Flexibility of service system to meet customer needs, Effectiveness of enterprise distribution planning schedule	Flexibility of service system to meet customer needs, Effectiveness of enterprise distribution planning schedule, Effectiveness of delivery invoice methods, Percentage of finished goods in transit, Delivery reliability performance	Quality of delivered goods, On time delivery of goods, Effectiveness of delivery invoice methods, Number of faultless delivery notes invoiced, Percentage of urgent deliveries, Information richness in carrying out delivery, Delivery reliability performance

Table 2.5 Supply Chain performance metrics framework

Beyond traditional process-oriented measures

Nowadays, companies are establishing more intense and active relationships with suppliers, focusing on new product development, integrating key processes and sharing information. Another contribution has been provided by Humphreys et al. (2007). They claim that, in such a new industry paradigm where strategic partnerships are more and more common and new product development has become a key process to integrate with the other actors of supply chains, customized design-oriented measure must be included in the supplier selection and evaluation process. However, a literature analysis indicates that design-oriented variables have been ignored in the past, as part of the supplier selection and evaluation process.

Talluri and Narasimhan (2004) provided a valuable contribution on the topic. They contribute by distinguish between strategic and commodity supplier. According to them, vendor selection criteria cannot be the same for the both groups. Hence, while commodity supplier could be evaluated only on operative performances, they argue that strategic suppliers deserve a more exhaustive set of attributes. Long -term strategic partners must be evaluated also on long-term attributes, such as *innovation capacity, quality management, design, new product development, knowledge development, concurrent engineering* (Talluri and Narashihman, 2004).

Furthermore, in modern Supply Chains the attention around environmental issues is growing rapidly. Pressures from market (Lamming, 1996), regulations and public are significantly influencing companies' strategic and tactical decisions (Humphreys et al., 2003). In their study, *Carter and Narasimhan (1996)* were among of the first to remark the role of purchasing in translate companies' environmental strategies into practical decisions.

In conclusion, the relevance of topics such as NPD and Sustainability is becoming more and more of major interest in purchasing organizations, it is obvious that the set of metrics must be adapted to cover these new topics. Thus, it is clear that establishing vendor rating criteria is not static but, instead, it is a dynamic and evolving process that must be more and more cross-functional and linked to corporate strategy.

This section aimed to provide the reader with an overview of the evaluation criteria discussed in literature so far. The outcome is a multi-faceted and complex reality that need a set of evaluation criteria that reflect this characteristic. This section wants to convey the message that such a uncertain and global business environment requires a customized set of metrics, designed following a top-down approach from strategic objectives.

2.4 Vendor Rating Data

This paragraph aims to discuss the vendor selection process taking a different perspective. The focus is not anymore on the macro view of the process but it is on the core asset that is exchanged throughout the process: data and information about suppliers' qualification and performances. In particular, constantly monitoring active suppliers generate a large repository of data that grows with day-by-day business. In the following lines, a brief overview of how information sources has been addressed in vendor rating literature. The paragraph end with some thoughts and insight about the issue of *disclosing* vendor rating data to other supply chain members.

2.4.1 Data sources and classification

Porter (1991), introduced a classification of the object of the evaluation. In fact, he defines *process-based* and *product-based* information, where the former focus on supplier's systems to track its operational issues and the latter is an ex-post evaluation on supplier's output (actual quality versus expected quality). It is implicit that each of these two Information Collecting strategy has different implication on the Behaving System. Another interesting classification of information collection mode is the distinction between *direct* and *indirect* information. The difference relies in the way they influence the overall evaluation process. *Indirect* information is information already processed, based on charts, reports and data about process performance. This implies that customer depends on the accuracy of this information. *Direct* information, instead, is characterized by a direct and active involvement of the customer in data collection. This implies face-to-face interviews, plant visit and first hand-observation (Daft and Langel, 1986). The following table by Surfi and Safayeni (2000) shows that, combining the two aforementioned classifications, a 2x2 matrix of possible information acquisition strategies is created.

Information Acquisition Mode	**Information Domain**	
	Process	*Product*
Indirect	Supplier provides customer with information about manufacturing and / or management processes.	Supplier provides customer with performance information (e.g., cost, quality, delivery)
Direct	Customer goes to supplier and examines manufacturing and management processes.	Customer tests outputs or collects its own performance data.

Table 2.6 Matrix representing Information acquisition mode

Each of the four strategies has advantages and implications. Every company should take advantages of using all of these strategies but, in reality the choice of the strategy to adopt is subordinate by two contingent variables: i) the nature of the relationship buyer-supplier; ii) the design of the manufacturing system. The *nature of the relationship* could be seen as the stability of the relationship. In fact, depending on the degree of the development of the relationship, the buyer could have access to a limited portion of information. For instance, if the relationship is new, it is likely that the buyer will not have access to *direct product information*, since they are reserved and representative of strategic decisions. On the other side, if a buyer-supplier relationship is well established and long-lasting, it is likely that the customer will have access also to direct product information.

Handfield et al. (2008) provide further insights about classification of information source that a buyer could use in the evaluation and selection process. In particular, they identified:

- *Supplier-Provided Information*: buyers always receive official data directly from potential supplier. This could be represented as the traditional

RFQ[29] to win an auction. In the past, they were considered enough to evaluate a supplier, while nowadays buyers require to perform additional analysis to have a complete picture.

- *Supplier Visits*: there are some intangible factors that are perceivable only through direct observation. Normally, a cross functional team performs a visit on-site to collect data. Some of the key evaluation criteria to note during a visit are: *management capability, organizational culture, total quality management, personnel relationship, environmental practices*.
- *External or Third-Party Information*: a buyer can acquire information on potential supplier's risk profile, financial stability and business performances through an external source such an information provider. This could represent a time-effective tools that buyers could use to complete the supplier's profile.

Managing this extensive amount of data coming from monitoring suppliers require the integration of technological supporting tools with firms' existing IT systems. In fact, technology is the essential enabler for vendor selection process and it facilitate information sharing and communication (Nudurupati et al., 2011). Luzzini et al. (2011) distinguish between three type of technological tools: i) *non-integrated platforms,* as Excel spread-sheet; ii) *ERP modules*, easily integrated with existing ERP modules but low customizable; iii) *Dedicated vendor portals*, highly customizable but hard to integrate with current systems.

2.4.2 Value of vendor rating data

It is common practice to claim that data about suppliers' performances are a valuable asset in buyers' hands. In fact, buying firm can constantly monitoring any attributes of the supplied items to ensure that the physical flow of goods works properly.

One of the key-issues of vendor rating is the exploitation of collected data about active suppliers' performances.

[29] Request For Quotation

Purdy and Safayeni conclude that, even though companies are able to collect information about suppliers from many sources, they struggle in integrating this information together and interpret these data to take strategic decisions. Thompson (1993) was one of the earliest to stress this point by stating that organization might have information about supplier's strategic decision but an integration with information coming from the shop-floor often lacks. Oper (1996) introduced an interesting view on this matter. He argues that companies are used to formally collect big amount of information about suppliers but they are not systematically used in supplier selection and evaluation process. As matter of fact, there is no evidence in literature that deal with the value of information collected through vendor evaluation and monitoring. Luzzini et al. (2014) conclude that *knowledge increased* is the root benefit that allow purchasing companies to pursue their own secondary objectives. In particular, they are: i) improve efficiency of purchasing process through a faster and better allocation of resources; ii) improving supply chain relationship with suppliers; iii) monitoring suppliers' performance to support decision making.

However, the value of supplier's performance goes beyond the sole benefit of improving buyers' purchasing decision making. In fact, there is some evidence in practice that also other stakeholders could benefit from the sharing of vendor rating data. On this purpose, a key-topic is the *communication and disclosure of evaluated performances*. Luzzini et al. (2014) claim that a purchasing company could decide to which extent disclose the collected information with other stakeholders. Thus, objects of the disclosure are either *indicators* (KPIs) or *scores*, or both. Sometimes, managers are not willing, or at least doubtful, in disclosing such information with suppliers. In fact, one of their major concern is that the disclosure would eliminate the existing *asymmetric information*[30], allowing suppliers to gain bargaining power in future negotiations (Luzzini et al., 2014).

[30] Asymmetric information, is present whenever one party to an economic transaction possesses greater material knowledge than the other party. This normally manifests itself when the seller of a good or service has greater knowledge than the buyer, although the opposite is possible. Almost all economic transactions involve information asymmetries. In this case the buyer is provided with much information about the suppliers than *vice versa*.

However, in today's context where establishing long-term strategic relationship has become a priority, there is empirical evidence that some purchasing companies take advantage by the disclosure of performance evaluation to suppliers, by obtaining an improvement of suppliers' performance.

On this purpose, the research stream of Supplier Development Programs (SDP) goes in this direction. SDPs are defined as *"activities undertaken by the buying firms in their efforts to measure and improve the products or service they receive from their suppliers"* (Prahinksi and Benton, 2004). In fact, buying firms can involve some of their suppliers in evaluation programs with the goal of motivating them in improving their performances and meet the objectives. This programs are based on the underlying assumption that the supplier would benefit from the disclosure of its performances by the buying firm (Prahinksi and Benton, 2004).

Many studies have focused on understanding contributing factors of SDP success or failure. Even though most of them consider SDPs a positive practice that can actually improve suppliers' performances, some scholars claim that there is not a direct connection between disclosure of vendor rating data and improved performances. Instead, several factors lie in between, for instance the *buyer-supplier relationship* and *supplier's commitment* to SDP (Prahinksi and Benton, 2004). In particular, Prahinksi and Benton (2004), in their empirical study, demonstrate that implementing supplier evaluation communication strategies is not enough to have a positive direct impact on supplier's performances. In fact, the commitment of the supplier and the type of relationship is a significant factor to obtain results. If the supplier is committed to the relationship and it is loyal, it is likely that the communication of operative performances within SDP could be beneficial for the supplier and, ultimately, for the buyer (Prahinksi and Benton, 2004). This is further confirmation that disclosure of vendor rating data could be not as straight-forward as it seems and it requires further investigation from scholars. Even though sharing vendor rating data has already been demonstrated to be beneficial for different parties, the existing literature has shown that it requires a careful and precise study in order to obtain significant benefits. As

It is possible to conclude that there is a huge amount of data, endowed with a significant intrinsic value whose potential has not been exploited yet. Those data are characterized by: i) *digitalization*, as they are already collected on digital supporting tools; ii) *formalization*, since companies have already set up rules and standards to make benchmarks possible; ii) *frequency,* as those data do not require additional investment by purchasing companies since they are collected on regular basis to secure their business. They represent punctual and complete information about supplier's operative status and, thus, they can be a *weak signal* for major problems, like financial distress or bankruptcy.

Purchasers must integrate risk analysis when assessing potential suppliers. Furthermore, a financial risk analysis is performed to assess the prospective supplier. Normally, they rely on third-party entities that provide a summary status of supplier's financial health. This is an important parameter to evaluate supplier because, in case of financial problems, the buyer could incur in supply disruption and this could lead to severe impact on business results (Handfield et al, 2008). This is an interesting point since, while an external entity providing access to information about supplier risk does exists, the counterpart for vendor rating performances is missing. As will be discussed later in the chapter, this is not due to a lack of information, since company systematically collect and store data about suppliers, but it is a matter of data sharing.

2.5 Research Gap

This chapter introduced the concept of Supply Risk and Disruption. Then, we have focused on a specific supply chain risk source: supply-risk and, in particular, *supplier's default*. We found that there is quite extensive literature on this topic and there is much evidence that avoid supplier's financial distress is a major concern for buyers, given the broad implication that it would have on Supply Chain behavior (e.g. default correlation) and decisions (e.g. single vs multi sourcing).

However, the first, and most important, research gap we found here is a little evidence in literature of the *value that vendor rating data have outside the relationship buyer-supplier*. In other words, it seems to be implicit that the "knowledge" that is generated inside the relationship, must remain within its borders. It has not been explored yet the existence of possible alternative application of vendor rating data, outside the traditional framework. There is some evidence of disclosure of vendor rating data inside the traditional boundaries of buyer-supplier relationship. However, there information sharing involving third-party actors (banks and financial institutions) has not been explored yet. This empirical study, based on the Italian SME context, aims to provide statistical evidence that vendor rating data are could be used as early signal to assess supply risk due to supplier's financial default.

To our knowledge, even though extensive literature address the creation of advanced and innovative dashboard for vendor rating management, there is no empirical and statistical proof of the value of vendor rating data in the creditworthiness assessment of suppliers. In the following chapter, the concept of Supply Chain Finance as a broader Supply Chain framework is introduced. We believe that Supply Chain Finance research can foster the development of this topic.

Another "grey area" in literature is about the *nature of SCM metrics*. In fact, most of the frameworks developed by authors comprehend a set of measures that are characterized by: i) *specificity*, because every proposal is industry-specific (e.g. Automotive, Weber et al. 1991) or considering only a limited vision of the whole problem (e.g. NPD or Environment); ii) *subjectivity*, because most of the measures that we encountered in our study must be subject to the interpretation of the results. In other words, there is lack of standardization and formalization in the topic. We are aware that every company should customize its own set of criteria that are most aligned with strategic decisions, but we have not found any attempt in academic literature to explore the path leading to a harmonization of vendor selection attributes. Our vision is that company should keep using tailored vendor rating model that match with their corporate objectives but some efforts toward more formalization and standardization should be done. We believe that formalizing vendor rating variable is a fundamental step towards the exploitation of the value of vendor rating data stored day-by-day by any buyer around the world.

A further gap identified is a lack of balance in the developed framework. In literature, there are many examples of balanced approach but the authors claim that manager are still focusing their attention on a single major area of metrics (Kaplan and Norton, 1992). In particular, the problem of assigning relative importance to any performance dimension is a problem that has been faced in literature. Furthermore, there is lack of statistical evidence on the significance level of different metrics. In fact, most of the empirical studies encountered in the literature analysis, use a qualitative methodology (e.g. AHP), often by survey submitted to purchasing managers or focus group. A statistical analysis would provide a sounder foundation would help identifying the most influent attributes.

A conclusive gap identified is a *poor integrated vision between operative performances and financial performances of suppliers*. Probably, the correlation between these two “worlds” is considered as obvious by many authors but we believe that it deserves further statistical evidence. A point that is made in this chapter is the difference existing between financial information and operative performances. Since financial data has been used widely in literature to evaluate firms’ performance, there are some third-party entities that monitor and keep updated the financial and risk profile of suppliers. However, since vendor rating data has been always treated as an internal asset of the buyer and not to be shared, these third-party actors are missing.

CHAPTER 3 - SUPPLY CHAIN FINANCE

This chapter provide insights on a promising and growing research topic: Supply Chain Finance (SCF). It is an innovation that have brought a new use of IT technologies, fostering collaboration between supply chains members and information sharing to create new way of financing supply chain operations without recurring to third-party actors outside the supply chain. The key-values that drive supply chain finance solutions are *transparency* across the whole supply chain and *collaboration* between actors to achieve win-win situations. It allows companies to diversify their funds sources and this is a valuable result, especially in the current market characterized by a credit crunch. The recent financial crisis has increased the difficulty for companies to obtain credit from financial institutions. Consequently, cost of debt went up dramatically. Such a critical situation required the development of innovative financing solution to master working capital throughout supply chains. For the purpose of this research, the key takeaway from this chapter is the growing integration between operational flows and financial flows throughout the Supply Chain. Following this trend, this study tries to provide evidence that Supply Chain perspective can improve effectiveness of creditworthiness models by integrating the two views.

3.1 Background and Supply Chain

World's changing rate has never been so high as it is now. As argued by Chen (2010), progress of network technology and economic globalization have constantly pushed businesses towards a division of labor: companies tend to focus on their core-competences and to outsource non-core operations in order to obtain cost-effective and higher-quality supply. Furthermore, Chen claims that customer demand has evolved rapidly and it has become complex and unpredictable: short product lifecycles and extreme customization are becoming the standard to satisfy customer's needs. It is common practice to state that competition is based on Supply Chains, rather than individual entities (Trkman et al., 2007). Mentzer et al. (2001) define Supply Chain Management as the "*collaboration and coordination of stakeholders to optimize the flow of goods, information and finance along the entire supply chain"*. Outsourcing wide part of operations to partners has become a more and more common (Varadarajan et al., 2001). Over the last decade, Supply Chain Management has gained more and more attention in the operations management field (Miller et al., 1981). First, it is important to introduce the following well-known definition of *Supply Chain Management* (SCM): "a process-oriented approach to managing product, information, and funds flows across the overall supply network, from the initial suppliers to the final end-customer" (Metz, 1998). From this definition, it is clear the strong focus on intra-company relationships that are fundamental to create identity and collaboration. Furthermore, it is to be underlined the heterogeneity of the exchanges that take place within the Supply Chain. As already illustrated in Chapter 1, *Supply Chain Finance* is a field that is focused on innovative way to exchange funds and finance investment along the Supply Chain. The focus of this Chapter is the information flow inside Supply Chain. In particular, since the focus of this study is Supplier's creditworthiness we will look mainly at first phase of the SCM, the so – called *Purchasing and Supply Management* (PSM) defined as "strategic approach to planning for and acquiring the organization's current and future needs through effectively managing the supply base" (Metz, 1998). The rationale behind the choice of focusing on this phase relies on the fact that PSM is an extremely information-intensive activity that generates huge amount of data that are regularly stored inside enterprises' information systems. According to several studies PSM has increased its relevance across every industry and has become more strategic and complex thanks to the existence of three macro-trends that are rapidly changing business organizations. First, *outsourcing* is pushing organization on focusing on its core-business and reviewing their whole make-or-buy strategies. Second, *globalization* is widening more and more Supply Chains' boundaries, pushing the limits farthest than ever before. Third, *e-business* is dramatically changing customer demand patterns and pushing companies in reshaping their strategy in order to keep the pace with this digital disruption (G.Spina et al., 2013; Norrman, Jansson, 2004).

The combination of these three factors leads to a new global wide supply chain where the number of suppliers has increased significantly, suppliers are scattered all over the world and the way in which customers require products change quickly. There are several consequences of this paradigm change but in this context, we will focus on two major findings: the heightened role of Purchasing due to its centrality and impact on strategic decision, and the complexity of managing relationships with such a high number of suppliers, located in any part of the worlds. This leads to another relevant topic in PSM: the proliferation of data due to the larger number of relationships, the higher complexity and the need of monitoring continuously in order to ensure a certain level of performances.

3.1.1.Financial flows in supply chains

At the beginning, Supply Chain Management was limited to traditional logistic and production collaborations (Lambert and Garcia-Dastugue, 2006) while nowadays a growing amount of literature provide evidence that Supply Chain Management can improve performances focusing also on demand sharing (Kahn et al., 2006), joint innovation (Autry and Griffs, 2008) and vendor development (Seetharaman et al., 2004). Physical supply chain is the processes by which goods are sourced, transformed and delivered to customers.

The word "finance" in the previous definition of Supply Chain could be expanded into a definition of *financial supply chain management*, defined by Wuttke et al. (2013) as "*optimized planning, managing and controlling of supply chain cash flows to facilitate efficient supply chain material flows"*. In other words, financial supply chain represents processes that support the physical supply chain in performing its operations and it can be defined a pillar of SCM (Mentzer et al., 2001). As Brealey et al. (2007) argue, management of cash flows is an important aspect of financial management. This support can come from credit assessment, financing and risk-mitigation instruments (Camerinelli, 2014). Financial supply chain comprehends the series of financial events (e.g. sending invoice to customer) and processes that are triggered by commercial transactions and that exchange both money and information (Lamoreaux and Evans, 2011). Its collaborative nature, implies the interaction between SC managers, with financial managers, suppliers, financial institutions and customers (Wuttke et al., 2013).

It is important to highlight the difference with financial flow management. In fact, the latter is the optimization of cash flow within the *single individual firm* while FSCM has a collaborative and inter-company nature. To sum up, main differences between FSCM techniques and traditional financial flow management are the following: i) focus (single firm vs SC); ii) goal (coordinated solution to optimized flows in FSCM); iii) stakeholder (banks, suppliers, customer in FSCM vs only inter-company) (Wuttke et al., 2013).

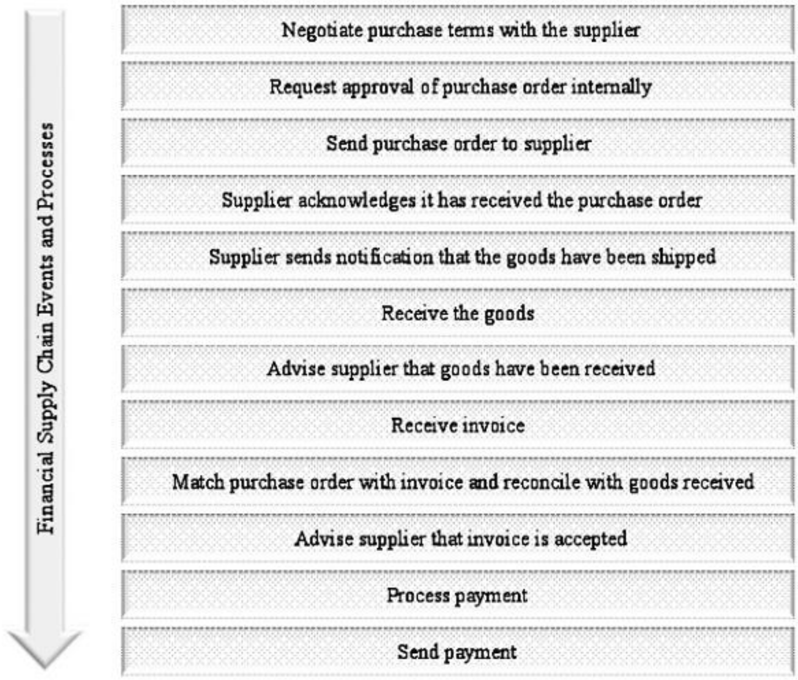

Figure 3.1 The "purchasing" financial process. (Source: Lamoreaux and Evans, 2011)

To sum up, three parallel flows throughout supply chain can be identified: material (physical), information and financial (Lambert and Pholen, 2001).

Among the three main "flows" that characterize a Supply Chain (product, information, financial resources), product and information flow has been aligned with great effort by companies in the past years (Bailey and Francis, 2008) while financial flows are still poorly integrated with the process (Wuttke et al., 2013). Lamoreaux and Evans (2011) argue that global supply chains' actors have provided great effort in improving and optimizing the "physical supply chain", acting on production, logistic and sourcing processes. Instead, little attention has been directed towards the supporting financial flows. Advanced and on-the-edge production and distribution processes are often supported by "traditional" financial instruments. Despite the scarce empirical focus of financial supply chain management, in literature there is plenty of evidence that supply chain financing costs have a relevant impact on COGS (Randall and Farris; 2009). A research by Aberdeen-Group (2006) estimated that financing supply chain costs account for 4% of total COGS.

3.1.2 Financial Supply Chain metrics

It is widely accepted to say that optimization of net working capital and C2C cycle are two key metrics to assess an effective financial flow throughout the supply chain (Camerinelli, 2014). For this purpose, these two key concepts are introduced. Both the two indicators utilize information taken by balance sheet and income statement. Working capital is the amount of liquidity that a company has available thanks to its day-by-day operations. It is built by three components: i) *account receivables (AR)*, that is the money that must be collected from customer because of a delayed payment terms; ii) *inventories (INV)*, that are the value held in stock by a company; iii) *account payables (AP)*, that represents money due to suppliers because of delayed payment terms; iv) *liquidity (LIQ)*, that is the cash available in companies' hands. Combining these four terms in formula, it is possible to obtain the Working Capital (WC) formulation, as follows.

$$WC = AR + INV + LIQ - AP$$

Working Capital must be accurately financed according to company's needs and objectives. In fact, it is an important metrics standing for the ability of a company of self-financing its day-by-day operations.

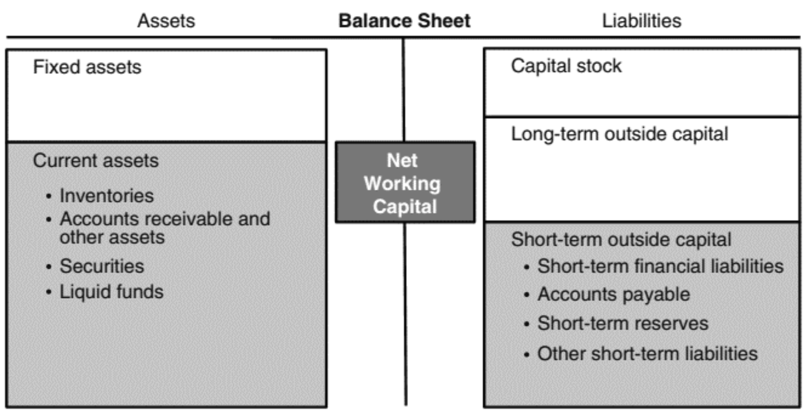

Figure 3.2: Net Working capital on balance sheet

The second important metric to benchmark is the *Cash-to Cash cycle* (C2C). This is a powerful instrument because it helps showing financial implications of decisions taken in the physical level of supply chain. This measure is used to calculate the time that lies between the moment liquidity exits that the company to pay suppliers and the moment the cash come back when customers pay the company (Lamoreaux and Evans, 2011). In this formulation, each component of Working Capital is transformed into its equivalent expressed in *days*. Proceeding in this way, we define i) *Days Sales Outstanding (DSO)*, it is the other side of AR and it represents the average number of days required to collect receivables from customer; ii) *Days in Inventory (DII),* is the time that an item spend inside production facilities before being delivered to customer, it is the duration of the raw materials' journey inside the company; iii) *Days payables outstanding (DPO)*, that is the arch of time available to company to pay suppliers. Behind each component there are several impacts caused by managerial decisions. For instance, a long lead time to receive inbound material would lead to a higher DII, while any problem occurring in the delivery of a product to a customer (damaged, late or wrong product) would have the consequence of a delay in the payment from the customer, thus the DSO would raise. For the purpose of this research, this introductory level will be kept. Now, the Cash-to-Cash cycle (C2C), the second key metric that show the relationships between physical and financial flows is introduced.

$$C2C = DSO + DII - DPO$$ [31]

[31] DSO, DII and DPO can be calculated as follows using a company's financial statements: DSO = (Accounts receivable / Sales) * 365; DII = (Inventory / Cost of goods sold) * 365; DPO = (Accounts Payable / Cost of goods sold) * 365.

The following graphical illustration helps understanding the meaning behind the C2C.

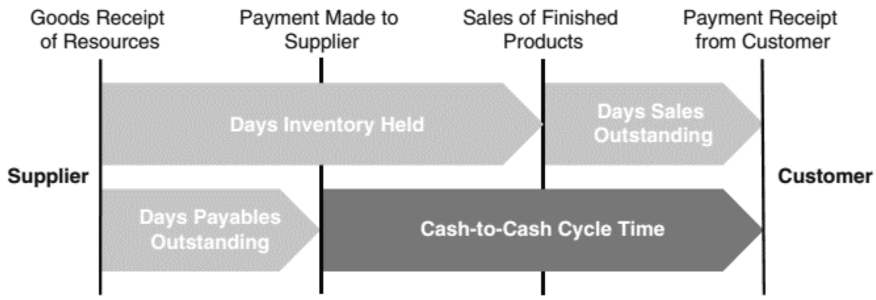

Figure 3.3: C2C cycle. Source: Ways out of capital trap

A short C2C means an effective SCM that leads to a lower risk and a lower need of external source of financing. Ideally, the company ultimate goal is to extend DPO, while minimizing DII and reducing DSO. In order to have some values to benchmark, a company that manage well its NWC is able to keep its C2C around 15 days, while inefficient firm can suffer a 100 day long C2C. Randall et al. (2009) point out that C2C can assume either a positive or negative value. Positive C2C means that a company ties up some liquidity for that specific amount of days, while Negative C2C, on the contrary, means that a company is holding capital. Another point made by the authors is that the optimal C2C cycle is not always 0, or negative. Instead, the determination of an optimal C2C value depends on the financial profile of the company. Thus, a company with a low cost of debt should have higher C2C days because it would cost less to access to debt to finance its operations (Randall et al., 2009).

3.1.3 After the financial crisis: challenges and risks of financial SC

The poor attention that SC managers has given to financial flows increased dramatically after the financial crisis (Lamoreaux and Evans, 2011; Polak et al., 2012). Before the crisis, accessing to credit was not a bottle-neck for corporates

(Polak et al, 2012) but the credit crunch, and the related *liquidity trap*[32], has decreased the potential for liquidity growth and this has pushed companies to focus on elimination of costs, risks and inefficiencies throughout the supply chain, improving cash availability and releasing working capital (Hofmann, 2013). In particular, risk related issues have become a priority for every company in the past years.

A first criticality of financial supply chain is that, given the impact of potential consequences, financial supply chain processes are highly formalized with many documents to be shared and approved by several actors, for each transaction. This makes the improvement of financial supply chain performances challenging (Lamoreaux and Evans, 2011).

However, the most important contribution to the growing attention towards supply chain financial risk is due to a specific phenomenon that has spread in supply chains consequently to the financial crisis. As Klapper and Randall (2011) illustrate, company with scarce liquidity started exploiting trade credit (leverage on payment terms with both suppliers and customer to forcedly reduce the Cash-to-Cash cycle). This phenomenon could be stressful for the stability of the whole supply chain because it is something that is passed upstream, until it is stopped by a company with liquidity (Boissay and Gropp, 2007). Some studies have shown that there is also a downstream "domino" effect of trade credit on customer chain (Coricelli and Masten, 2004). Corporate bankruptcy happens when liabilities overcome assets and, in such an inter-connected market, default of a SC member may cause consequent defaults, called *bankruptcy diffusion* (Battiston et al., 2007). Another important contribution was provided by Gatti et al. (2006). They discovered that credit interconnections between firm are cause of bankrupt diffusion because of consequent failure to pay debts. Archibald et al. (2002)

[32] a situation, described in Keynesian Economics, in which injections of cash into the private banking system by a central bank fail to decrease interest rates and hence make monetary policy ineffective. A liquidity trap is caused when people hoard cash because they expect an adverse event such as deflation, insufficient aggregate demand, or war. Common characteristics of a liquidity trap are interest rates that are close to zero and fluctuations in the money supply that fail to translate into fluctuations in price levels.

stressed the gravity of cash-shortage for SMEs while Sullivan et al. (1998) empirically demonstrated that 28% of all business bankruptcy were due to financing reasons. Xu et al. (2010) have investigated the mitigation of bankruptcy risk through supply-chain coordination. Their research demonstrates that supply chain coordination is effective in reducing risk of bankruptcy. In particular, some collaborative solutions are found to be important in risk mitigation, but they require some additional incentive to one party because there is asymmetry in benefits. Lamoreaux and Evans (2011) explain this problem as the predisposition of SC's actors to "improve their financial position at the expense of *upstream* or *downstream* blocks". They claim that large buyers have leveraged their higher bargaining power by "squeezing" liquidity out of account receivables (reducing payment terms) and, at the same time, reducing both account payables (paying suppliers later) and inventories (last-minute orders and deliveries).

As shown by this introductory paragraph, there is plenty of improvements areas in financial supply chain flows. In the last decades, many actors like trade finance banks and technology information providers have been developing innovative financing solution to optimize financial flows and mitigate risk throughout supply chains (Lamoreaux and Evans, 2011).

3.2 Supply Chain Finance

3.2.1 Definitions

In this section of the paragraph, the concept of SCF is formally introduced. According to Camerinelli (2014), there is still confusion and a missing common language to define SCF and the market terminology. Furthermore, the market of SCF is evolving rapidly. Consequences of this changing environment is a lack of a general accepted nomenclature.

As we have already mentioned before, SCF is a multi-faced discipline, involving different perspectives and actors. According to this, it is clear that also definitions can vary from one author to another. A valuable contribution is provided by Gelsomino et al. (2016). In their work, they state that is possible to classify definitions of SCF according to two dimensions: i) the role of financial institutions and ii) the scope of SCF (Reverse Factoring only, Inventory optimization, Fixed assets financing). The *role of financial institution* is relevant because some author attributes a major role to them, as active actors of SCF providing solutions, while other author do not focus on this vision. The *scope of SCF* is about how authors consider the nature of SCF. In other words, each definition sets larger or narrower borders of SCF depending on the scope they see for SCF solutions.

The definition provided by Hofmann (2005) is synthetic and complete: "*Located at the intersection of logistics, supply chain management, collaboration, and finance, 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*".

However, from the literature, there is evidence that SCF has been addressed following two major stream: i) finance oriented and ii) supply-chain oriented. Furthermore, a third category of SCF definition could be identified within the Financial-oriented perspective: buyer-driven perspective.

Perspective	(a) Role of financial institution	(b.i) Scope: only RF	(b.ii) Scope: inclusive of inventory optimisation	(b.iii) Scope: inclusive of fixed asset financing
Financial oriented	Mandatory	No	No	No
Buyer-driven	Mandatory	Yes	No	No
Supply chain oriented	Non-mandatory	No	Yes	Sometimes

Table 3.1 Supply Chain Finance perspectives addressed in literature

Another relevant definition is provided by Pfohl and Gomm (2009). They define SCF as the "*inter-company optimization of financing as well as the integration of financing process with customers, suppliers, and service providers* *in order to increase the value of all participating companies".* The author claims that the ultimate goal of SCF is to save capital cost using mutual adjustment and innovative financing concepts within supply chains.

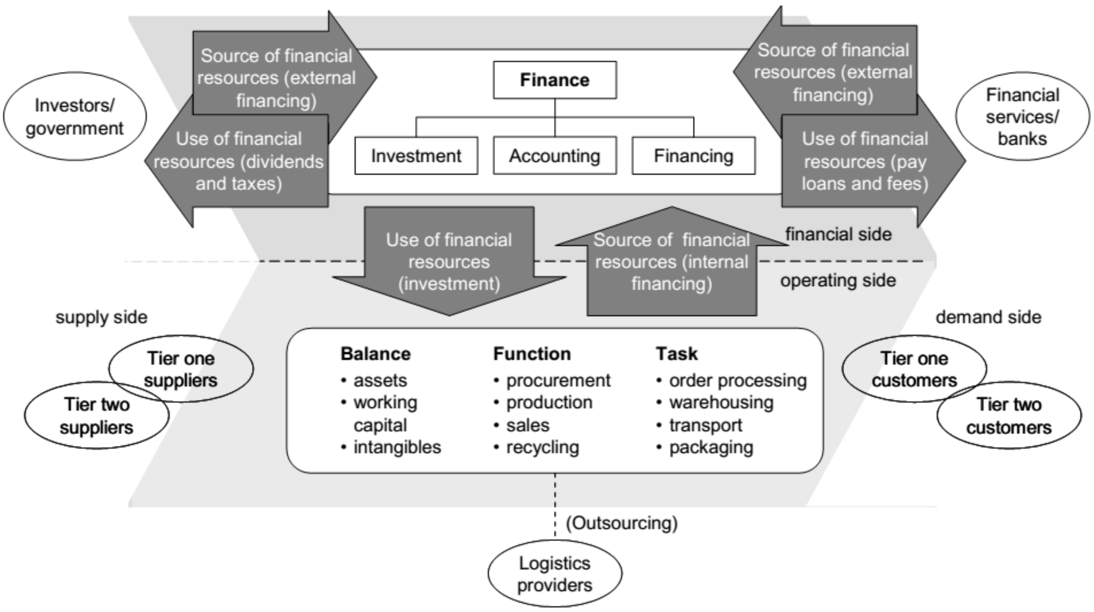

Figure 3.4 Hofmann (2005)

Finance-oriented perspective

Finance-oriented definition consider SCF solution as a short-term solution provided by financial institution (**Camerinelli, 2009; Hu, 2011**). In this model, given the active role of financial institutions, the focus is more on payables and receivables, and less on inventories. A furhter contribution on the topic has been provided by More and Basu (2013) who have created a framework to classify SCF solutions that will be presented the following sections of the chapter. Financial perspective is short-term oriented and extremely focused on a limited number of SCF instrument (e.g. Reverse Factoring) (Caniato et al., 2016). Lamoureux and Evans (2011) claim that SCF solutions are triggered by specific "milestone" in the trade process as *order confirmation, shipment, invoice and payable due date).* Camerinelli (2014) states that SCF is "event-driven", meaning that in financial supply chain, every action is driven by a correspondent event in the physical supply-chain.

Inside the finance oriented perspective, it is possible to identify a sub-perspective called *buyer-driven perspective*. It is modeled as a specific set of cases where the SCF solution is triggered by an action made by the buyer. In literature (Seifert, 2010; Wuttke et al., 2013) this perspective has often been modeled as an upgrade of the Reverse Factoring solution. Some authors (Chen and Hu, 2011) argue that this "evolution" of Reverse Factoring is mainly due to the technological innovation that has favored transparency across the supply chain, provide access to capital to more suppliers at a lower cost of debt.

Supply chain-oriented perspective

This is the opposite perspective of finance-oriented one. As already mentioned, these definitions focus on a major scope of SCF solutions: the net working capital[33] optimization across the whole supply chain. Here, the financial institutions do not have always a primary role, but they rather play an ancillary role (Gelsomino et al., 2016). In this approach, SCF solutions comprehend actions that move and shift inventories between different actors of the SC, affecting the *C2C cycle*[34]. Supply chain – oriented perspective deals with decisions on working capital in every component (payable, receivable and inventories) and ways to finance them together with fixed-assets (Caniato et al., 2016). On this perspective, Randall and Farris (2009) contributed by analyzing benefits stemming from a shift of inventories between two different supply chain's actors.

[33] The formula for net working capital (NWC), sometimes referred to as simply working capital, is used to determine the availability of a company's liquid assets by subtracting its current liabilities.

[34] The cash conversion cycle (CCC) is a metric that expresses the length of time, in days, that it takes for a company to convert resource inputs into cash flows.

No.	Article	Definition
1	Hofmann (2005)	SCF is an approach for two or more organisations 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 inter-organisational level
2	Camerinelli (2009)	SCF is the set of products and services that a financial institution offers to facilitate the management of the physical and information flows of a supply chain
3	Pfohl and Gomm (2009)	SCF is the inter-company optimisation of financing as well as the integration of financing processes with customers, suppliers, and service providers in order to increase the value of all participating companies
4	Gomm (2010)	(SCF is the process of) optimising the financial structure and the cash-flow within the supply chain
5	Chen and Hu (2011)	SCF, as an innovative financial solution, bridges the bank and capital-constrained firms in the supply chain, reduces the mismatch risk of supply and demand in the financial flow, and creates value for supply chain with capital constraints
6	Lamoureux and Evans (2011)	SCF solutions represent a combination of technology solutions and financial services that closely connect global value chain anchors, suppliers, financial institutions and, frequently, technology service providers. They are designed to improve the effectiveness of financial supply chains by preventing detrimental cost shifting and by improving the visibility, availability, delivery, and cost of cash for all global value chain participants
7	Grosse-Ruyken *et al.* (2011)	(SCF) is an integrated approach that provides visibility and control overall cash-related processes within a supply chain[a]
8	Wuttke *et al.* (2013a)	We define (FSCM) as optimised planning, managing, and controlling of supply chain cash flows to facilitate efficient supply chain material flows[b]
9	Wuttke *et al.* (2013b)	(SCF is) an automated solution that enables buying firms to use Reverse Factoring with their entire supplier base, often providing flexibility and transparency of the payment process[c]
10	More and Basu (2013)	(SCF) can be defined as managing, planning, and controlling all the transaction activities and processes related to the flow of cash among SC (supply chain) stakeholders in order to improve their working capital

Table 3.2 Literature review of main Supply Chain Finance definitions

3.2.2 SCM Framework

A specific framework for Supply Chain Finance has been developed by Pfohl and Gomm (2009). The scope of the framework is provide a methodological scheme to evaluate SCF solutions in a structured way. The authors focus their attention on three main dimensions: *assets (objects), actors* and *levers*. In the Figure 3.5, it is shown the three-way SCF framework.

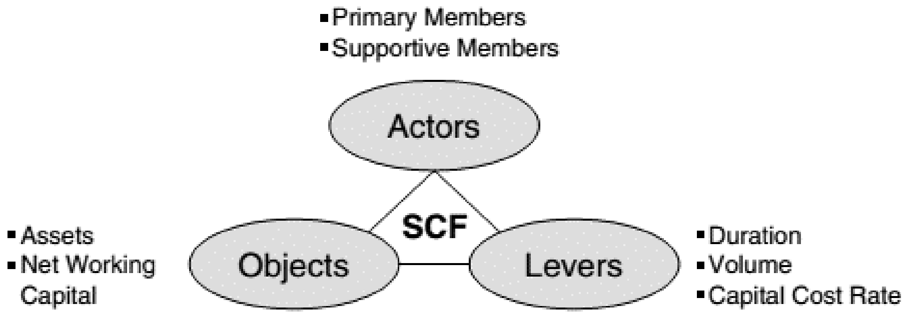

Figure 3.5 The three-way SCF framework

SCF Objects

They represent the scope of the financing. They can be both *fixed assets* instruments that a company keep for more than a year), or *net working capital* (1.1.2). Examples provided of fixed assets that need to be financed are: production facilities, equipment and machines. Working capital represents current assets that are translated into cash within one fiscal year. As already introduced in the previous paragraph, the related C2C indicator, is a key-metrics to evaluate financial performance of supply chains.

SCF Actors

Since SCF has a strong collaborative foundation, the definition and classification of main involved stakeholder seems to be important. SCF actors are the stakeholders of SCF solutions. Lambert et al., (1998) grouped SCF actors into *primary members,* that are focal company, customers, suppliers; and *supporting members,* like logistic service providers. Pfohl and Gomm (2009) argue that, if one translate the concept of Supply Chain into "delivery of financial capital", the role of financial institutions, even though they play the role of financial service providers and they would be classified as "supportive" by Lambert's classification, is a key-role and, thus it cannot be considered a secondary one. The introduction of innovative financial intermediaries is replacing traditional financial intermediaries. Pfohl and Gomm (2009) argue that SCF turns supply chain actors into intermediaries that can partially resolve the problem of asymmetric information between banks and capital borrowers.

SCF Levers

Any SCF solutions must be evaluated depending by the impact on SC performances. For this reason, it is extremely important to understand which are the levers that SCF has to create value for the Supply Chain. In detail, dimensions of SCF follow three different directions:

- *Volume of financing*: the amount of liquidity that is financed
- *Duration of financing*: for how long the financing will last
- *Capital cost rate*: the cost to access debt

By multiplying the former three terms together, it is possible to obtain a value-oriented measure of SCF impact, the *capital costs*, as follows:

$$Capital\ Costs\ [€] = Volume\ [€]\ \times\ Duration\ [time]\ \times\ Capital\ cost\ rate\ [\frac{\%}{time}]$$

An important consequence of this formulation is the graphical translation of it into a model. The combination of the three dimensions lead to the construction of the *SCF cube* (Pfohl and Gomm, 2009).

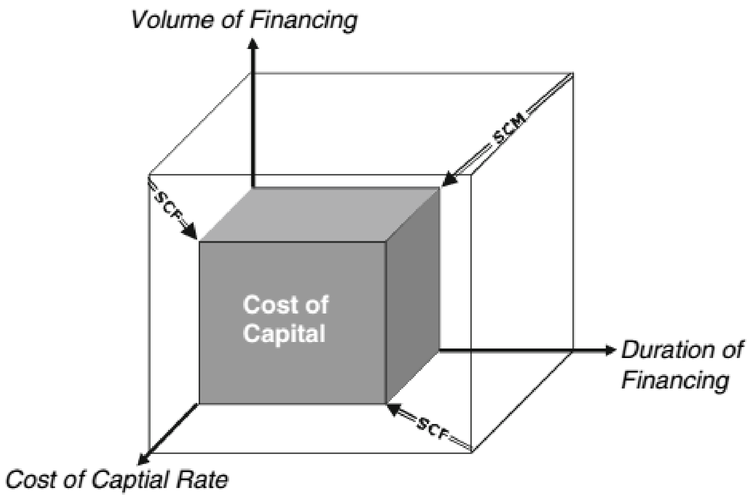

Figure 3.6 SCF cube (Pfohl and Gomm, 2009)

As already mentioned in the chapter, SCF solutions aim to reduce Cost of Capital across the entire supply chain. In this sense, this framework is useful because it helps understanding the single contribution that each dimension brings to the final outcome. As shown by the arrows in the figure above, SCM can have a positive impact on reducing cost of capital, but it can exploit only two dimensions (volume and duration) and its levers are mainly related with production and logistic innovative solution that lead to a lower need of financing. On the other side, SCF has two arrows on two plans. This means that SCF must implicitly consider the effect of cost of capital rate as lever to improve cost of capital (Pfohl and Gomm, 2009)

3.3 Supply Chain Finance solutions

A structured introduction to Supply Chain Risk will be carried out in the Chapter 3 (Supply Chain Perspective) Furthermore, there is extensive literature on Supply Chain Risk, but still poor contributions to study the risk source of unbalanced financial flows (Caniato et al., 2016). However, sometimes there is still confusion about the difference between *SCF solutions* and *trade finance solutions*. While the former consists in financing suppliers through loans or factoring to help them perform their operations, the latter represent an innovative set of alternatives instrument that allow suppliers and buyers to access cash in a different way (Lamoreaux and Evans, 2014). During mid-2000s, Boissay and Gropp (2007) suggested that a possible solution to stop the problems of trade credit chains would be allocating liquidity in the largest company of the supply chain and then let it lend money to other member of the supply chain. This could be considered an approach that coexists with SCF solutions. Hofmann (2005) claims that SCF solutions must be driven by the following guidelines:

- Dematerialization and automation: elimination of paper to foster financial flows;
- Transparency: driven by a shared platform provided by external sources that increase visibility;
- Predictability: meaning easy access to various data;
- Control: thanks to transparency and predictability, identification of exceptions, control mechanism;
- Collaboration: creation of win-win situations with suppliers, encouraging also collaboration within firms;

According to the existent literature, in this moment of the SCF development, it is common practice to cluster SCF solutions into three groups: i) *Traditional financing solutions;* ii) *Innovative financing*; iii) *SCC Solutions* (Caniato et al., 2016).

Traditional financing (i) solution group includes those applications that do not require advanced digital capabilities and massive IT systems integrations. Typically, they are *captive factoring* and *traditional reverse factoring*. *Innovative financing (ii)* solutions are an "upgrade" of the former group since they need a strong digitalization of processes. Examples are *advanced reverse factoring, inventory financing, dynamic discount, seller-based invoice auction*. Finally, *SCC solutions (iii)* deal with the supply-chain oriented perspective of SCF. Their main objective is to optimize net working capital through a wide collaboration and information sharing among actors. Given the diversity and wideness of SCF solutions, it would be impossible provide an introduction to all of the them in this work. For this reason, we have selected a sample of the most popular and implemented solutions to present. Following, among the traditional SCF solutions, Reverse Factoring is presented; among innovative SCF solutions Dynamic Discounting and Inventory Finance are presented; and among SCC solutions Vendor Managed Inventory (VMI) is presented. Each solutions is introduced by describing the purpose, the actors, the concept and the key-benefits.

Reverse Factoring

This solution represents the most explored in the past and the most frequently used in practice nowadays. According to the classification provided by Caniato et al. (2016), Reverse Factoring (RF) is considered one of the traditional SCF solutions. The key drivers of this SCF solutions are large buyers that usually represent the strongest link of the SC. The rationale behind this method is relatively simple: thanks to buyer's safer risk – profile, it has access to capital at a lower cost of debt. In this solution, the buyer provide access to its cost of debt also to its supply base. In this way, suppliers could benefit from accessing to credit through a lower cost of debt. In other words, Reverse Factoring enables a supplier to receive a discounted payment of account payable that must be paid by a buyer.

A key requirement for the application of this solution is that the buyer must have a cheaper cost to access the capital. In fact, the bank trusts the creditworthiness of the buyer while suppliers are interested in being involved because it could exploit both an easier access to financing and a the buyer's higher credit rating (Camerinelli, 2014).

According to Lamoreaux and Evans (2014), many large buyers started these solutions with the ultimate goal of improving the financial stability of upstream blocks of the supply-chain. A key-enabler of this solution is a shared technology platform where suppliers can ask to a financial institution to be financed as soon as some financial supply chain events take place. Once the buyer accepts the invoice produced by the supplier, it triggers the financial institution that receive the request for payment. Thus, the financial institution can transfer funds to the suppliers and, at the maturity of the receivable, the buyer will pay back the financial institution directly. In the following scheme, is represented the reverse factoring process.

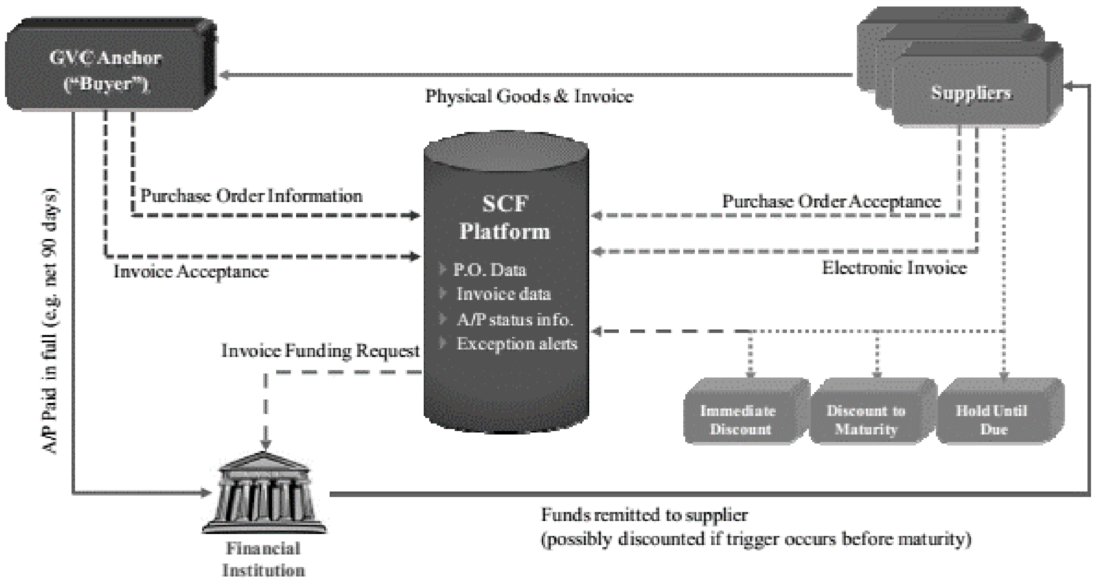

Figure 3.7 The reverse factoring process

Regarding reverse factoring, it is important to distinguish between two types of application, depending on the event that triggers the intervention of the financial institution. Thus, it is possible to identify two separate approaches:

- *Pre-shipment arrangements:* in this case, the financial institution decide to transfer funds to the supplier before goods are produced and shipped. For instance, the involvement of the bank could be triggered by the acceptance of the purchasing order by the supplier. This solution is intrinsically more complex and it brings additional risk to the financing bank because some unexpected event could impact the process. In fact, financial institutions will discount account receivables of suppliers with a higher discount percentage than post-shipment solutions. For instance, suppliers might have to face a disruption that would not allow the on-time delivery of goods or buyer could decide to change its order. For all these reasons, *pre-shipment* reverse factoring is preferably applicable in well-established relationships.
- *Post-shipment arrangements:* this represents the most common version of reverse factoring that have been implemented in practice. Here, the *triggering events* is not the confirmation of the purchasing order, as in the pre-shipment arrangements; while the process starts only when goods have been delivered and the buyer approve the invoice. This scenario is less risk for the financial institution because operative and distribution risk sources are removed.

Benefits stemming from reverse factoring are numerous and different for suppliers and buyers.

There are some benefits that are common between suppliers and buyers. Those advantages have impact on a supply chain level, as follows:

- C2C duration decrease
- Cost of debt decrease
- Collaborative relationships are established
- Stability and competitiveness of SC improved
- Better cash flow forecast thanks to increased visibility

Some benefits are exclusive to *suppliers*:

- Possibility to discount account receivables in less time and more easily
- Exploit buyer's lower cost of debt to obtain cash
- Reduction of Days Sales Outstanding

Some benefits are exclusive to *buyers*:

- Increased Days Payables Outstanding and reduction of Days in Inventories
- Elimination of cost to process supplier's payment

Theoretically, *reverse factoring* has been described in literature as a win-win situation and the previous list is in favor of this vision. Furthermore, benefits appear to be unbalanced in favor of the supplier, even though many benefits are present for the whole SC. Thus, according to Van der Vliet et al., (2013), it is possible to identify two different buyer-centered strategies: i) *return-oriented strategy,* the buyer seeks mainly cash flow benefits by extending payment terms (DPO) or reduction in purchasing costs (Liebl et al., 2016); ii) *risk-oriented strategy*, where the buyer benefits indirectly of reverse factoring, improving the relationship with suppliers, simplification of invoicing process and risk mitigation of up-stream supply chain (Liebl et al., 2016).

However, some studies have tried to investigate what are main drivers of reverse factoring benefits, taking the supplier perspective. In fact, Liebl et al., (2016) and Martin & Hofmann (2016) claim that is not so obvious that suppliers would obtain certain benefits. Instead, since reverse factoring is a *buyer-driven* solution, the buyer is always aware of its benefits and they represent a strong motivation for the buyer to involve suppliers into reverse factoring. De Goeij et al. (2016), analyzed the supplier perspective in RF through several case studies to understand what are the drivers and condition to allow a supplier obtain real benefits from a RF solution. Their results show that supplier must be aware of actual consequences of this solution in order to drive better the negotiation and gain advantages. Once the supplier receives a proposal of starting a RF solution with a buyer, it should evaluate the impact of the following dimensions: i) cashflow; ii) financing costs; iii) current forms of financing; iv) collaboration with buyer. Sometimes, if the supplier trusts the buyer and accept the solution without analyzing actual impact on its results, it may lead to a deterioration of supplier's cash flow (De Goeij et al., 2016).

Dynamic Discounting

According to Caniato et al. (2016), *Dynamic discounting* is classified as an innovative financing SCF solution. It offers to suppliers anticipated payment of payables due by the buyer, in return of a discount. The opportunity of the birth of this SCF solution come from the way suppliers have traditionally offered discount to buyers. In fact, discounts on invoices have been usually based on some pre-determined combination of discount rate and payment due date. For instance, a common discount formula says "2/10, net 30". This means that the supplier would offer to the buyer a 2% off on an invoice that was supposed to be paid in 30 days from now, but the buyer will pay in 10 days (Camerinelli, 2014)

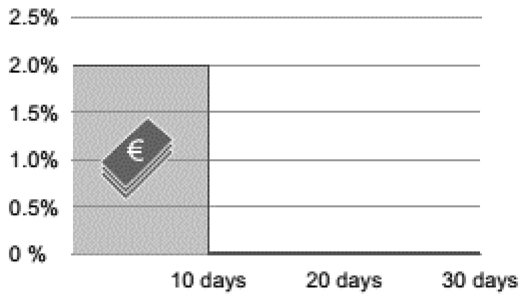

Figure 3.8 Dynamic discount (Camerinelli) "2/10, net 30 formula"

This solution hides some inefficiencies and appears to be too static (Camerinelli, 2014). For example, if the buyer fails to process the invoice within 10 days (taking the 2/10, net 30-days discount), the supplier will not offer the discount because this traditional process is very rigid and strict.

For this reason, dynamic discount was conceived. In the following figure, the process of dynamic discounting is presented. The key-concept in dynamic discounting is that both the parties negotiate on payment terms and create a continuous sliding scale with infinite combination of payment days and discount on invoice. Dynamic discount can be defined as an *"ICT-based evolution of common trade credit policies that allows the dynamic settlement of invoices in a* *buyer-supplier relationship. 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"* (Caniato et al., 2016). This approach requires both supplier and buyer to connect to a shared platform to optimize the timing of invoice payments. In some cases, the supplier has the right to adapt the discount rate along the invoice life-cycle to drive the moment of payment.

One of the main benefits is that buyers can have less variability in the discount they received, being able to plan and control their supply chain better. Buyers have a clear visibility of the impact of their decisions (when to pay an invoice) on their economical results. However, buyers do not see a decrease in their working capital. On the supplier side, there is a faster access to cash at acceptable rates, and a reduced uncertainty of payment date (Nienhuis et al., 2013).

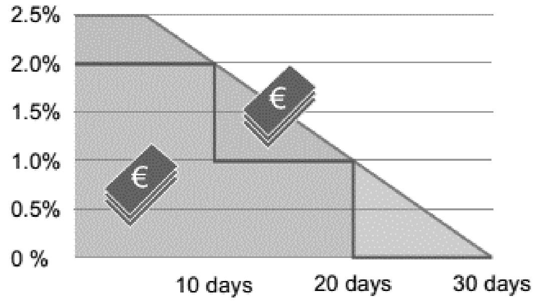

Figure 3.9 Dynamic discounting

For every invoice at any time, buyer and suppliers could agree on a certain combination of discount and advanced payment date. This increase flexibility but require a robust IT infrastructure like electronic invoice system that increase speed of invoicing process. In fact, this solution can be defined as a *peer-to-peer* situation where no third-party actors are necessarily involved (Nienhuis et al., 2013). Somehow, Dynamic Discounting could be seen as the dynamic version of invoice early payment, that is a static mechanism of discount on invoices based on pre-determined set of combinations.

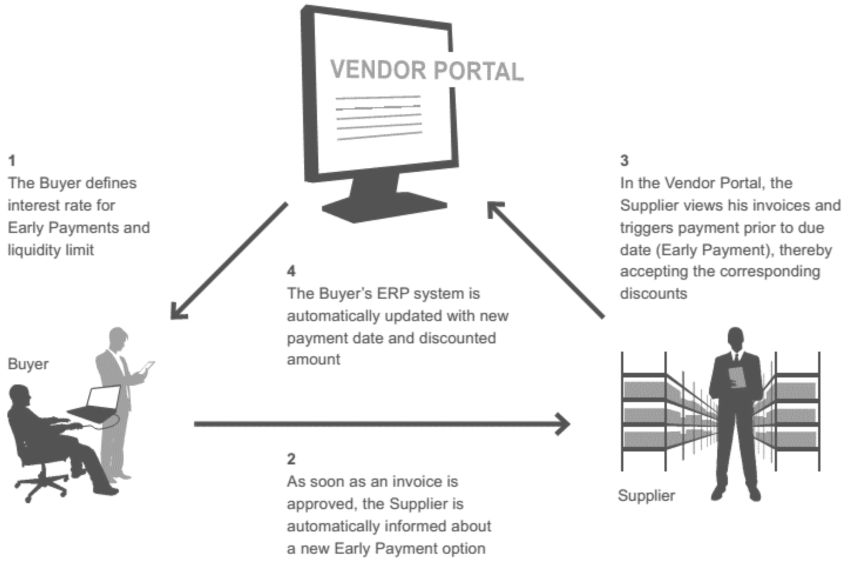

Figure 3.10 Dynamic discount (Camerinelli)

Inventory finance

Inventory finance is an innovative SCF solution in which goods are financed and the banks receive security interest over them. Prior literature, suggested that inventory financing was free. This assumption has been discredited because it has been demonstrated that working capital must be financed, either internally or externally. In particular, firms that have to pay suppliers in a shorter term than is paid by its customer, need their stocks to be financed. A good example is all the products that contain tomatoes as raw material. In fact, due to its intrinsic seasonality, companies must buy stocks of tomatoes in advance and this represent a large cash outflows that the company has to bear, months before cash will flows back inside the company through sales. In fact, Otherwise, they will risk to face liquidity shortage.

In inventory finance, stocks are used as *collateral*[35] but they have to meet some conditions in order to be accepted as collateral. Normally, banks accept to finance inventories that are "marketable" because, first, it is easier to estimate their value and, second, the bank could re-sell them on the market. For this

[35] In lending agreements, collateral is a borrower's pledge of specific property to a lender, to secure repayment of a loan.

reason, applicability of this solution is limited to qualified commodities (raw materials such as metals) or finished goods because the market value can be deducted by buyer's purchasing orders or buyer's cost accounting registers). Work-In-Progress stocks are not qualified to take part of this SCF solution because their poor "marketability". (Camerinelli, 2014). A further condition for a stock to be marketable is their intrinsic value. This means that banks do not accept stocks that are slow-moving goods or are subject to obsolescence. In fact, those stocks have poor value and the bank must protect itself by the risk of a potential default of the debtor. In other words, Inventory Finance is the SCF method of securing a business bank loan with on-hand inventories as collateral. However, Inventory Finance requires a high involvement of the lending institution in the knowledge of the borrower's supply chain. This additional investment could be complicated if the lender has not already an expertise on business processes.

In Inventory Finance, the mechanism is simple: two main actors are involved, a borrower and a bank. The financial institution finances supplier's stocks in advance to reduce its net working capital, using stock itself as collateral of the financing. The repayment of the credit can take place in different ways, the most common is that the suppliers pays back a part of the credit every time the customers purchase from the supplier. In this way, from the supplier's viewpoint cash inflows and cash outflows are aligned. Sometimes, the bank could take advantage of a third-party logistic provider that would "operatively" take care of stocks during the financing period.

Vendor Managed Inventory (VMI)

VMI belongs to the category of SCC solutions. In fact, they have a strong collaborative perspective that is the value-creator of the solution. Waller et al. (1998) define it as the process where the supplier take care of inventory replenishment on the behalf of its buyer, monitoring inventory levels and regularly updating re-supply decisions about order frequency and volumes, shipping and timing. This solution gained popularity in the '80s and became popular in the grocery industry characterized by agility and quick response. The buyer leaves control and key decisions of resupply inventory to the supplier. Here, some pitfalls of VMI could arise. In fact, the problem of choosing the right supplier is not an easy task. It may take some time for a supplier to organize its operations to support this new process and to set up supplied quantities correctly. Sometimes, the ownership of the stock remains to the suppliers, even though inventories are physically delivered to the customer, until they are used or sold by the buyer (Waller et al, 1998). In the following table, main upsides and pitfalls of the four Supply Chain Finance solutions are summed up.

Type	Pros	Cons
Reverse Factoring	Suppliers obtains immediate access to cash. At the same time, the buyer has agreed to be ultimately liable and the interest rates are based on the credit of the buyer, which are usually much lower.	Credit availability for the supplier can fluctuate with credit of the buyer. It is also a complicated approval process subject to differing laws in various regulatory jurisdictions. Supplier on-boarding can be complex.
Dynamic Discounting	Suppliers improve cash flow situation. Invoices are paid immediately. It is a win-win situation for both buyer and supplier. Easy on-boarding. The involvement of a third-party financial institution is not required. But, if invoices are financed by a financial institution, the customer can be kept out of the solution, with an increased transparency.	Using invoices as collateral could make harder to get conventional ways of financing. The buyer does not decrease its working capital.
Inventory Finance	Possibility to free cash flow that is tied up inside on-hand inventories. It takes place in the short-term (one full year) and it can be transformed into a line of credit if the loan was successful. IF does not have impact on "debt" book value on balance sheet, thus it does not reduce the access to alternative traditional source of finance	Information about record of sales and value of inventory must be shared with financial institution. Limited application on business with tangible and physical stocks and with high inventory turnover rates. Banks are required to know the peculiarities of borrower's supply chain, in order to understand stocks.
Vendor Managed Inventories	Increased collaboration in the supply chain. Higher visibility of end-customer demand leads to a optimization of stocks level across the SC.	Supplier's higher responsibilities carry higher administrative costs to set up new processes. It may take some time to tune the correct supplied quantities.

Table 3.3 Pros and Cons table of main SCF instruments

3.4 Supply Chain Finance benefits

Given the heterogeneous nature of SCF solutions, expected benefits reflect this variety. Apart from solution-specific benefits that have been presented so far, this paragraph aim to sum up general benefits from a wider perspective. Several different categories of benefits are found in academic literature.

Financial benefits

However, among the different expected benefits there is a benefit source that has been investigated more than others: the difference between cost of capital between actors of the same supply chain. The exploitation of this gap is considered the major foundation of most SCF benefits (Lamoreux and Evans, 2011). In absence of this fact, most benefits would have poor effect. This issue has been explored broadly in the earliest works in the field of SCF (Randall and Farris, 2009; Brennan et al.,1988; Pfohl and Gomm, 2009).

In order to introduce the other benefits, other dimensions must be included in the analysis: the *financed capital* and the *duration of the debt*. The combination of the three benefit factors introduced so far *(difference in cost of debt, financed capital and duration*) has been analyzed by Pfohl and Gomm (2009) in their work where they created a framework to evaluate every SCF solution existent at that time along those three dimensions. For instance, Vendor Management Inventory (VMI) has a direct impact on financed capital while Reverse Factoring has a double powerful effect on both *duration of the debt* and *cost of debt gap* (Dong et al., 2007; Farris and Hutchinson, 2002). A further financial benefit is related with increased profit due to a reduction of financial costs through solutions as dynamic discounting models (Nienhuis et al., 2013; Polak et al., 2012).

Supply chain benefits

Exactly like definitions of SCF follow two parallel perspectives, also the benefits reflect the same structure. In this section benefit related to supply chain are presented. Many authors claim that obtaining *visibility* and *transparency* across the Supply Chain would be an interesting possibility (Pfohl and Gomm, 2009). The increased visibility would allow the largest companies up-stream in the supply chain to have higher comprehension of the end-customer demand.

Klapper (2006) provide an important contribution in stating that there is another benefit source coming from SCF solution. The object of his work is the *reduced risk of bankruptcy throughout the supply chain*. This benefit is obtained through Factoring and Reverse Factoring solutions. The point made by the author argues that suppliers with a high-risk profile would benefit from these solutions by mitigating their risk level thanks to the lower buyer's risk. According with the author, benefits consist in a lower cost of debt, an easier access to funds and a minor risk of supply chain disruption due to supplier's distress.

Reverse Factoring would bring another important advantage in term of overall SC performances. In fact, financial institutions prefer collect receivables from big and safe buyers on which they can easily collect data, rather than collect receivables from a large number of small suppliers. This would facilitate the task of financial institutions that would benefits from this solution in terms of time and resource needed.

However, financial institutions would benefit from SCF solution also in another way, by improving their risk-assessment process directed to SMEs (Deakins and Hussain, 1994). Hoffman (2005) claims that SCF would improve the availability and quality of exchanged information. This is a particularly interesting topic for this research, since the role of exchanged data

3.5 Supply Chain Finance challenges and future

Supply Chain Finance is a relatively new discipline and the attention of both companies and the academic world is growing rapidly. Since it is still in its early phase of life-cycle, some obstacles to the diffusion of SCF solutions are present. In this section, main challenges for SCF will be pointed out and, for each challenge, a brief outlook to potential future development will be carried out. To help the reader, we specify that, in structuring the following presentation of challenges, we will refer to the one provided by Lamoureux and Evans (2011), that divide them into *demand-side*, *supply-side* and *technology & regulatory*.

Demand-side

From the last empirical studies conducted on the market, it is shown that there is still a lack of understanding by both suppliers and buyers of the concept and the potential benefits of SCF solutions. Together with this, implementation of SCF solutions require a robust change in SC operative processes and this have to face numerous resistances to change by actors. Finally, since SCF solutions can provide significant potential benefits, they are not cost-less. Especially, buyers have to invest money and time to promote SCF solution and involve willing buyers into them.

However, on one side it is true that there are some obstacles to the growing demand, but it is also true that large buyer with strong purchasing power has put in place great efforts in the last year to obtain as much liquidity as possible out of the working capital, using traditional trade credit solution. For this reason, there is little space left for them to persist with "conventional" approaches because it seems that a "structural limit" for further improvement of C2C cycle has been reached (Demica, 2010). This is a promising sign that the demand for SCF solutions with naturally grow in the next future.

Supply-side

If from demand-side there is still a mix of bias and skepticism that is not allowing innovative SCF solutions to grow as they were expected to do, on supply-side a first criticality is that there is still a limited number of financial actors ready and willing to offer SCF solution, and an even smaller group of actors able to provide end-to-end SCF solutions to companies. Furthermore, banks are seeing their margins being eroded. Thus, they need a potential large volume of demand of SCF solution to be able to invest in profitable business. As far as risk exposure is concerned, banks decide to implement a SCF solution with a buyer that meet the minimum requirement of risk-level. Furthermore, banks have shown scarce interest in financing (and thus being exposed) both downstream (distribution financing) and upstream (inventory financing). Another point is the contact that banks have with companies, that is often limited to finance department while a growing involvement of procurement function would be more appropriate for an optimal deployment of SCF solution.

As per demand-side challenges, also for supply-side there is some expected future evolution. However, in the offer of SCF solutions, more obstacles are present. In fact, in the post-crisis context, banks must be very prudent in employing their capital and the strict Basel III contribute to this restriction. Furthermore, the low rate of return that characterize SCF solution does not foster the involvement of banks and does not increase the offer of SCF platform. The possibility of growth for SCF solutions depends on how much credit capacity banks will allocate on them. A positive expectation for the future is the fact that bank would benefit from the development of SCF solution because they would obtain a diversification of credit exposure in their risk portfolio. In the supply-side, a key role is performed by non-bank financial institutions. In fact, they will be the real engine of the development of SCF solutions.

Technology and Regulatory

First, there is a lack of standardization of SCF platforms regarding banks, technology service providers. This leads to a higher complexity and cost for users.

Furthermore, a strong automation is missing in connecting financial flows with physical flows within supply chains. There is the issue of ensuring security of automated financial transaction. In fact, there is still low trust and confidence in the legality and security of e-transactions. Some accounting practices and regulations must be adapted to SCF solutions environment. For instance, sometimes payables involved in reverse factoring solution were considered as bank debt. This is a further obstacle to the spread of SCF solutions.

The future of technology in SCF is critical for the adoption of innovative financing solutions. The first forecast is that, in the short and medium term, there will be on the market many non-compatible platforms because many actors (corporations and banks) have invested in SCF technology and so they want to recover from these investments. In the long run, a common standard platform will raise from the rest and it will make cheaper for companies buy state-of-the-art technology, instead of developing in-house platforms. In other words, a reduction of the number of different SCF platform is expected in the medium and long term. As far as automation is concerned, major improvement will be visible in the integration between financial and physical flows. In fact, the adoption of e-invoicing and the progressive elimination of paper-based documents will be fostered by the kick-off of many initiatives. The first step will be the creation of regional standards.

3.6 Research gap

Supply Chain Finance represents a new discipline in the academic world and, even if interest is growing around it, literature is still scarce. In fact, the first research gap we identified is a *lack of common theories in SCF*. Since it is an evolving discipline in its seminal phase, it is normal that different perspectives and models are built. For instance, as already mentioned in the discussion, two main perspectives exist in SCF: financial oriented and SC oriented. This parallel development does not contribute to the harmonization of concepts and to the creation of shared theories. Individual efforts have been provided by single authors to create structured framework but a common language is missing. However, this research has not the ultimate goal of creating a solid background theory for SCF and, thus, this gap will not be addressed in the following chapters.

A second gap is literature has been found in a general *lack of robust empirical analysis* on the interaction between supply chain performances and financial performances. From a theoretical viewpoint, interaction between the two dimensions has already been addressed but a solid and robust statistical analysis is missing. Limited to our sample of Italian SME, the present study aims to investigate the nature of the correlation and its intensity, in order to draw some conclusions about inner potential of this new framework.

The third research gap regards the information that are generated in the development of supplier-buyer relationships. As already introduced within the previous chapter, data that are collected by buyers on suppliers' behavior represent a valuable and exploitable resource.

This is true for at least three reasons: i) those data are already digitalized because the activity of monitoring suppliers is normally integrated with companies' IT systems; thus, they are almost ready-to-use information; ii) those data are collected systematically, on a daily or weekly basis; thus, information is always updated; iii) a high degree of reliability characterizes those data; in fact they are used by the buyer firm itself to support decision-making.

However, the potential value that this knowledge has outside the relationship has not been deeply explored yet.

For the purpose of this research, we highlight that an integration between financial and supply chain world can be obtained through the creation of an integrated creditworthiness model that will be introduced and discussed in detail in the following chapters.

CHAPTER 4 - DATA COLLECTION AND RESEARCH FRAMEWORK

4.1 Data collection

The data collection process of this research has been complicated and time consuming. In order to perform our analysis, three kinds of data have been included: *financial data, vendor rating data and credit rating data*. The optimal situation would be having a complete database in which every company is provided with all those kinds of data at the same time. However, in our case, some data has been more difficult to retrieve than others. The data collection strategy has been the following: first a sample of 1000 companies has been exported from the credit rating database; secondly, these 1000 companies have been matched with vendor rating database and the outcome was a sample of around 140 companies populated with both credit rating data and vendor rating data. Finally, the resulting sample have been matched with the financial database. This iteration hasn't reduced furtherly the sample size because the financial database doesn't represent a bottleneck.

Therefore, in the data collection process, several samples have been identified. The reason behind this variety of samples is that not all the research questions need each typology of data in order to be completed. Thus, we decided to use different samples, each one compliant to the requirements of the specific research question. In this way, each research question has been supported by the largest sample possible, in order to provide reliability and validity to the results. In the following sub-paragraphs, each type of data will be briefly introduced.

4.1.1 Credit Rating data (Source: *BPER Banca*)

Since the main topic of the present research is on credit scoring models, the first step of the data collection process was to retrieve as much as possible companies endowed with traditional rating data assigned by a financial institution. Among all the collaborations that Politecnico di Milano has in place with companies and financial institution, the relationship with BPER Banca has been exploited to obtain a sample of companies populated with credit rating information. BPER Banca is a top commercial, universal and cooperative bank and is the parent bank of the BPER Group, ranked among the first banking groups in Italy primarily focused on small and medium enterprises with a strong international vocation. Each company retrieved from the BPER Banca database is characterized by the following information:

- Credit rating (years 2014-2015)
- Probability of default (years 2014-2015)

  The extraction from the database is characterized by 1006 companies.

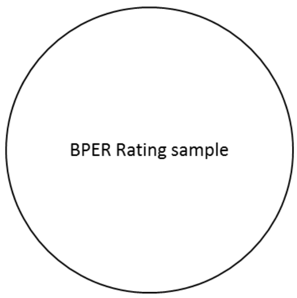

Figure 4.1 First step of Data collection process: financial data from BPER Banca

4.1.2 Vendor Rating data (Source: Niuma)

Retrieving vendor dating data was the second step of the data collection process. Vendor rating data has been the hardest ones to be collected for many different reasons such as:

- *Confidentiality*: not every buyer is willing to disclose vendor rating data with external stakeholders.

- *Vendor Rating data are not mandatory*: there are no laws that regulate vendor rating disclosure.

Given the hardness to find comparable and reliable vendor rating data, they have represented the real bottleneck in the data collection process.

Niuma is the information provider in charge of supply vendor rating data to this research, thanks to its collaboration with Politecnico di Milano. Niuma is an innovative Information Technology company founded in 2002. The Company has a specific division dedicated to providing highly specialized solutions in the field of procurement through the development of an e-procurement IT platform. NIUMA has provided us with the vendor rating of the suppliers of 13 different buyers:

BAYER	COSMI	FIERA MILANO	ICBPI	MSC	SANOFI	SIGMA
CESI	CVA	GDF	JANSSEN	NTT	SIA	

Table 4.1 Buyers that have supplied vendor rating data

All the VATs numbers[36] retrieved from NIUMA have been matched with the BPER database. The result of this matching is a sample of companies that are populated with both vendor rating data from NIUMA and credit rating data from BPER Banca. The following figure shows the match performed at this step of the data collection process between BPER Banca sample and NIUMA sample.

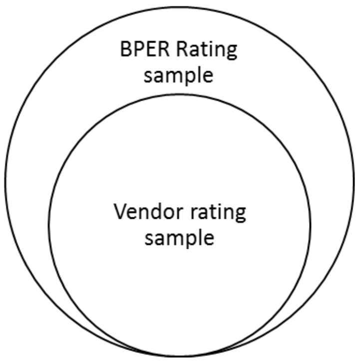

Figure 4.2 Second step of Data collection: Matching BPER Banca with Niuma

[36] Italian: Partita IVA

4.1.3 Financial data (Source: Bureau van Dijk's AIDA)

As widely mentioned in Chapter 1, financial information are the real pillars of any credit scoring model because they well represent the company's health. In order to have the most complete set of financial information possible, Bureau van Dijk's AIDA database was selected as the source. AIDA is a well-known data provider on quantitative and qualitative information on Italian companies (e.g. financial statements, company description) which provides user with a high degree of customization in search design strategy. AIDA imports data from companies' financial statements and it indexes them providing access to users. Companies exported from AIDA are characterized by any kind of financial data coming from the following documents:

- Balance Sheet items (Assets & Liabilities)
- Profit & Loss items
- Financial flows information

Financial data do not represent any bottleneck in the data collection process, in fact every company that is present in the BPER Banca database or in the NIUMA one, is also on AIDA. In the following figure, they are represented as the bigger outer circle that include both the other two samples.

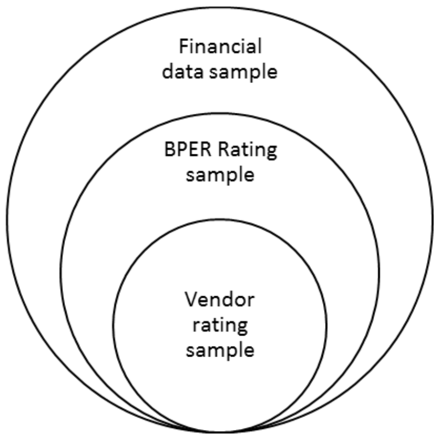

Figure 4.3 Final step of Data collection: BPER Banca, Niuma and AIDA

4.2 Research framework

Chapters about literature review have the main scope of introducing the reader to the topic of the research and to present the analysis of the state-of-art. The outcome of the literature review is the identification of the research gaps that will be formalized in this section in the form of research questions. The formulation of the research questions is a key-step in an academic research. The research questions are the practical translation of the research gaps. In the end, each research question has been addressed with a specific research methodology.

For this reason, it is of high importance to ensure that research gaps, research questions and research methodologies are all well-connected together. Figure 4.4 shows the steps that we have done in defining the research framework.

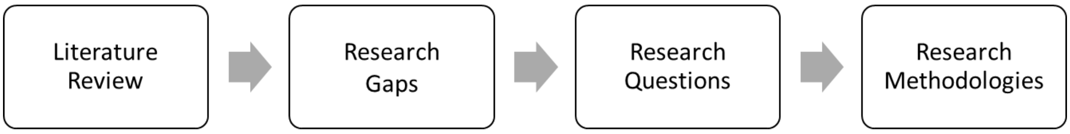

Figure 4.4 Steps of the research framework

The rest of the chapter is structured to follow the logical process just introduces. First, a literature review summary is presented in order to highlight the research gaps that have arisen. Then, the definition of research questions is introduced. It is given high importance about how each question respond to one or more research gaps with the aim of ensuring the value of the present study. Finally, an introduction of used research methodologies is presented. It will be discussed the rationale behind the choose of each methodology and how it applies to each research question.

4.2.1 Literature review summary and Research Gaps

Chapter 1 aims to introduce the reader into the topic of creditworthiness, starting from the historical roots and illustrating the main milestones, represented by the Basel accords, that led to the current set of definitions, requirements and consequences that financial institutions look at. Linked to that, a definition of credit rating and credit scoring has been provided. The chapter ends with a systematic overview of the main statistical models supporting the credit scoring definition found in literature. It represents a picture of the evolution of credit scoring models over time. Finally, the improvement of performances of credit models is briefly discussed.

Given the wide literature on this topic, the review on creditworthiness has provided several inputs for this study. Numerous theories have been found and many collateral issues are present in literature. However, the main output has been the identification of some gaps in the literature that have not been investigated yet. In particular, the main takeaway of the first chapter is that credit scoring models have been of great interest for scholars and a plethora of frameworks and quantitative models can be found. However, the focus has been pointed only on improving modeling techniques rather than feeding existing models with new data. This has led to marginal improvements in performances of models, so the attention should be, now, shifted on finding additional sources of information to assess creditworthiness. The main research gap coming from this chapter shows that current models are supplied only with financial and economic information taken from companies' financial statements. Even though there are some scholars that have stressed the importance of introducing new sources of data, there is a lack of empirical analysis on this topic.

Chapter 2 tries to identify a new source of information to be introduced in credit scoring models. The focus of this chapter is on the vendor rating data, that are information that buyers systematically collect about suppliers' performances on time. This data is used by buyers with many aims, such as: keeping track of supplier's performances to have early signals of potential supply problems and creating knowledge to support future decision-making process on supplier selection and evaluation. The chapter starts with the definition of Supply Chain Risk and Vulnerability. This broad initial perspective allows the reader to have a little familiarity with the concept of Supply Chain Risk. More in detail, the consequences of supplier's default have been analyzed from the Supply Chain perspective, investigating the impact that such event would have on the whole network of companies. Afterwards, the supplier evaluation and selection process has been introduced with particular attention on vendor rating data. The chapter ends with a deep digression about the value that vendor rating data has once they have been captured by buyers. The result is that, nowadays, buyers seem not to exploit the hidden value of vendor rating data. They normally keep vendor rating data for internal use, supporting decision-making, or sharing them with suppliers through programs called Supplier Development Program (SDP). The key research gap that comes out from this chapter is that there is no evidence in literature of any attempts to exploit the value of vendor rating data outside the borders of the supplier-buyer relationship. Those data have a hidden potential since they are collected systematically on a regular basis, and they are already stored in buyers' ERP systems in a digital format.

The goal of Chapter 3 is twofold: first, introducing the reader into the new discipline of Supply Chain Finance (SCF) providing definitions, frameworks and information about the current development of literature; second, providing the SCF as a common point between the two perspectives discussed previously. In fact, principles of SCF are taken from both sides and the main objectives is the optimization of financial flows throughout the Supply Chain. This can be achieved exploiting innovative and alternative way of financing capital internally among SC actors. After a brief discussion about what are financial flows in Supply Chain and why the proper management has become a priority after the financial crisis, the topic of SCF is introduced. A literature review on the status of SCF definitions and framework has been presented. Afterwards, a review of the main SCF solutions is carried out together with a comparison of solutions and challenges of each method. Finally, an outlook to the future of SCF is presented with existing trends and initiatives. The main research gap that has been identified in this section is a lack of common, structured framework among researches. This results in several independent perspectives that slightly different with each other. Furthermore, there is a lack of empirical study that try to combine these two perspectives to provide benefits to the whole supply chain.

In conclusion, Table 4.2 presents the main research gaps that have been identified in the literature review.

RESEARCH GAPS		
Credit Rating	**Vendor Rating**	**Supply Chain Finance**
Lack of transparency in the creditworthiness assessment process	Lack of proof of vendor rating data value outside supplier-buyer relationships	Lack of a common structured framework
Lack of supply-chain perspective in assessing creditworthiness	Lack of empirical analysis of predictive value of vendor rating	Few empirical analysis of integrated approach

Table 4.2 Summary of research gaps for each topic from the literature review

4.2.2 Research questions

Once Research Gaps have been discussed and formalized, Research Questions are declared.

RQ0: Understanding determinants of credit rating

The first issue, that the present research wants to address, is about the problem of the lack of transparency in the process of creditworthiness assessment by financial institution. As already pointed out in literature, credit rating is determined starting from two main set of information, which are combined together to create the credit rating. These two fundamental "bricks" are financial data and qualitative data. There is wide acceptance in literature that financial data has the largest weight in the assessment of credit rating. Given that the final goal of this thesis is the development of a supply chain-oriented creditworthiness framework, this first research question aims to provide some insights about the determinants of credit ratings.

Therefore, the first research question could be formulated as follows:

RQ0: *"Are credit scoring models consistent with credit rating ones? How much is the credit scoring's weight in the determination of the final credit rating?"*

This first research question can be considered as an "introductory hypothesis" since it paves the way to the next steps of the research. The name itself "RQ0" is self-explanatory: this question has the goal of build solid foundations for other two hypotheses that constitute the real "core" of the work. The objective of this question is twofold: first, it aims to understand if any credit scoring models show inconsistent behavior with the credit rating ones; second, it allows to test the extent to which credit scoring (financial data) determines the credit rating.

Statistically speaking, the relative correlation of these two dimensions "Credit Scoring" and "Credit Rating" has been investigated. The goal of RQ0 is to provide insights about both the *direction* of the correlation ("*Are credit scoring models consistent with credit rating ones?*) and the *intensity* of the correlation ("*How much is the credit scoring's weight in the determination of the final credit rating?*). The following figure helps to clarify the first research questions.

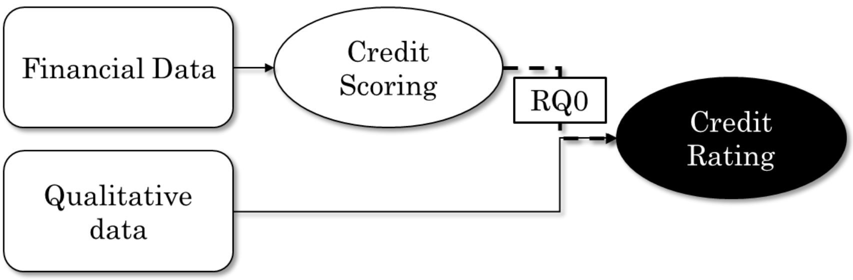

Figure 4.5 Visual representation of RQ0

In this case, BPER Banca and AIDA database have been matched to obtain the largest sample as possible. In the following figure, a visual representation of the matched sample is provided.

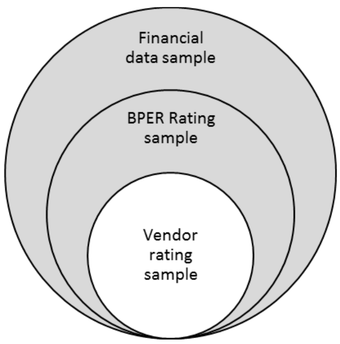

Figure 4.6 Sample used in RQ0

RQ1: Evaluating the potential of Vendor Rating data

The second research question introduces the innovative component of the research: vendor rating data. The aim is to analyze the relationship between vendor rating data and the rest of the data that are already present in the model. The reason why this research question has been included in the study is that, every time there is the possibility of introducing new variables into a model, several considerations about the incremental gain of model performance must be performed. In other words, it must be discussed whether the introduction of a new source of data in a credit rating model would bring additional information or not. If the addition of this kind of information resulted redundant, it would mean that almost all the informative potential is already explained by some other variables already present in the model. The following figure is the graphical representation of the second research question. The goal is to demonstrate if the information included in vendor rating data are already present in credit scoring model or in credit rating ones.

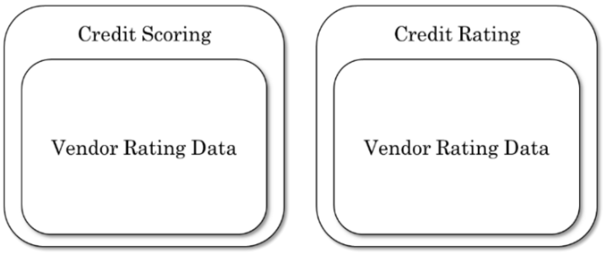

Figure 4.7 Visual representation of RQ1

In fact, although vendor rating data and financial information are two independent concepts, with different measures and actors, it could be that financial data variability already reflects the vendor rating one, making the introduction of the latter unnecessary. Therefore, the second research question is formulated as follows:

RQ1: *"Would vendor rating data be redundant in a creditworthiness assessment model?"*

In RQ1, all three categories of data have been included in the analysis. The companies in the sample are populated with data of each source of information.

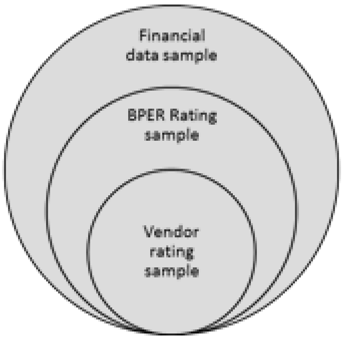

Table 4.3 Sample used in RQ1

RQ2: Integrated supply-chain oriented creditworthiness model

In the first and the second RQs, the focus was on having an understanding about how the credit rating is built (RQ0) and whether vendor rating data could represent a missing piece of information that would improve effectiveness of creditworthiness assessing models (RQ1). The third research question represents the last step of this research and it aims to provide an innovative contribution to the existing literature on this field. In the following figure, it is graphically reported the structure of the research questions. The relationship marked with a dotted line in the figure below represents the real missing brick in literature.

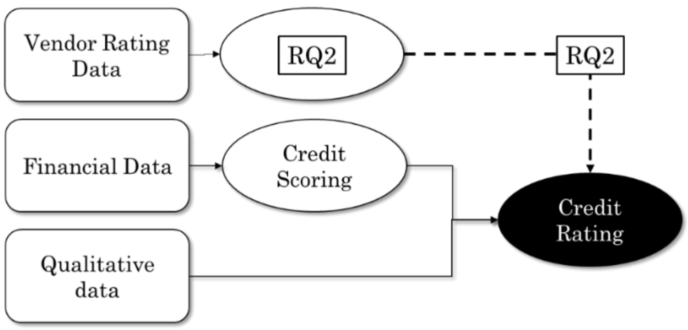

Figure 4.8 RQ2 structure

In the figure, the label RQ2 is put on two parts of the diagram. This is because this research question is addressed to solve two different issues.

The first goal is to identify how vendor rating information can be aggregated in order to be used in credit rating models. Given that these data are characterized by a poor degree of homogeneity and a lack of standardization, an intermediate step is required. There is the need to design a way to elaborate vendor-rating data with the objective of improving their usability and facilitating their integration inside existing credit rating models.

The second goal of this research question is about developing a new credit rating framework that includes, also, this new source of information to assess companies' creditworthiness. This research question discusses also whether this integration would be meaningful or not. Therefore, the third hypothesis could be formulated as follows.

> **RQ2:** *"Is it possible to develop a "supplier rating"? Would the introduction of vendor rating data improve creditworthiness models?"*

This research question covers the majority of research gaps that were found in literature, so it represents our innovative contribution. Each question has been designed as a step towards the final objective. However, each step has its own value as itself.

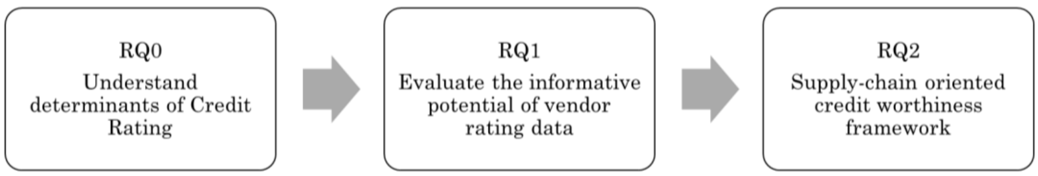

Figure 4.9 Step-by-step representation of the logical connection between research questions

In particular, RQ0 analyzes the existing credit rating model to understand relative importance of determinants in credit rating. Then, RQ1 tests whether vendor rating data can bring an informative gain in the value of the model if they are not already included in financial data. Finally, RQ2 is the real innovative core of the research and it leads to the formulation of the TO-BE framework. The final goal is to demonstrate that the addition of vendor rating data would improve the effectiveness of credit rating models. It is worth to underline that this is an on-the-edge topic since there is no evidence in literature of any attempt of this kind.

4.2.3 Research methodologies

The final step of the research framework is represented by the choice of research methodologies. In detail, four different methodologies have been applied. In the following table, a summary of all the methodologies is presented. For each methodology, a brief description is reported, together with the research question that the methodology points to.

Research methodology	Description	Research question
Literature review	Identification of research gaps	Formulation of RQs
Statistical models	Correlation matrixes ANOVA Student's t-tests	R0/R1
Visual Data analysis	Two-axis comparative matrixes	R1
Focus Group	Three-rounds workshop with experts	R2

Table 4.4 Research methodologies with details and related RQs

Literature review

First, a review of existing literature (academic papers, research journals and books) is needed to understand the state-of-the-art, to identify latest trends and to spot research gaps to address. Practically, the methodology has followed three different perspectives: *financial, vendor rating* and *supply-chain finance*. For each topic, great effort has been put in place in order to collect and analyze several sources of information on the matter. As already discussed, literature review is a fundamental methodology in every research work, as it is the starting point to define following steps. Thus, the main contribution of literature review is the formulation of research questions that followed the identification of research gaps.

Statistical models

Once research questions have been formulated, data collection process started and data has been collected from three different sources (*AIDA*, *Niuma* and *BPER Banca*) to build samples to perform statistical analysis. The second research methodology, *statistical models*, include different tools such as correlation matrixes, ANOVA and Student's t-tests. These statistical tools have been used to investigate correlations and differences between variables to support the discussion on RQ0 and RQ1.

Statistics is the science of collecting, analyzing and making inference from data. Statistics is a particularly useful branch of mathematics that is used by researchers in many fields to organize, analyze, and summarize data. Statistical methods and analyses are often used to communicate research findings and to support hypotheses and give credibility to research methodology and conclusions.

In the following table, a summary of the statistical techniques implemented is reported. More details will be provided in the following chapters where the punctual explanation of the statistical procedure is reported.

RQs	**Statistical model**	**Variables**	**Description**
RQ0	Correlation matrix	• Credit scoring • BPER Rating	Analyze correlations between credit scoring models and the credit rating
	ANOVA	• Z''-Score • BPER Rating	Analyze differences of credit rating between risk-ranked clusters according to Altman'' model
RQ1	Correlation matrix	• Vendor Rating • BPER Rating • Z''-Score	Analyze correlations between Vendor Rating data and the other variables in the model
	Student's t-test	• Z''-Score • Vendor Rating	Analyze differences of vendor rating performances between high-risk and low-risk companies according to Altman'' model
	Student's t-test	• Cluster BPER • Vendor Rating	Analyze differences of vendor rating performances between high-risk and low-risk companies according to BPER rating model

Table 4.5 Details of statistical methodologies

In order to support the statistical analysis, a visual data analysis has been performed. The rationale behind the choice of including visual tools in the analysis is linked to the fact that that are able to provide a different perspective of the same problem.

Focus group

In this research, a theory-building methodology has been followed. In detail, RQ2 has been responded via a *Focus group* and this choice will be briefly introduced in this paragraph. Powell et al define a *focus group* as a group of individuals selected and assembled by researchers to discuss and comment on, from personal experience, the topic that is the subject of the research. The effectiveness of this methodology relies on interactions between the group participants on a certain topic proposed by the researchers (Morgan, 1997). The results of the *focus group* are insights or data produced by the participants that can support or deny the thesis proposed by the researchers. Merton and Kendall's (1946) specified that the participants must have a specific experience of or opinion about the topic under investigation. In this way, the outcomes coming from focus groups acquire validity. Focus group is preferred to other methods, such as observation, one-to-one interviewing, or questionnaire surveys because its main purpose is to draw upon respondents' attitudes, feelings, beliefs, experiences and reactions in a way in which would not be feasible using other methodologies. Focus groups are particularly effective when the participants are different in terms of: culture, industry provenance and power level. Focus groups can be used at the preliminary or exploratory stages of a study (Kreuger, 1988); during a study, perhaps to evaluate or develop a specific program of activities (Race et al 1994); or after a program has been completed, to assess its impact or to generate further avenues of research.

The focus group has been performed in the form of a workshop structured in three sessions. The organization of the focus group has been possible thanks to the collaborations that the *Osservatorio SCF* has in place with many external actors. In each meeting, all the participants joined an interactive discussion about the agenda of the day. Directors and coordinators of the *Osservatorio SCF* acted as moderators in the discussion. The participants to the Focus group were members belonging to different departments of manufacturers, banks and institutions. Table 4.6 summarizes the list of the companies that took part to the focus group.

Partecipant	Role	Partecipant	Role
ACMI	Business Development Manager	**CRIBIS**	Marketing
ADACI	Vice-President Regione Lombardia	**Frinsa**	CFO
Ariston	Procurement Director	**FS2A**	Owner
Assolombarda	Financial Credit director	**Groupama**	Financial Analyst
Banca Sella	Innovation manager	**Industrie Saleri Italo**	Supply Chain Manager
Boldrocchi	Investment Manager	**Niuma**	Technical Manager
BPER Banca	Marketing	**Sanofi Aventis**	Chief Procurement Officer
Bticino	Chief Procurement Officer	**AvantGarde Group**	Analyst
Caruso	Chief Procurement Officer	**Thomson Reuters**	Governance Risk and Compliance
Cerved	Marketing		

Table 4.6 Focus group participants

As it is possible to see from the table above, the panel of participants of the focus group consisted of a wide range of profiles belonging to different kind of organizations. This is a typical requirement for research methodologies such as *focus group*. In fact, heterogeneity is favored as a mean to foster diversity and thus stimulating creativity.

The focus group was broken into three meetings:

- First meeting (14/07/16): Environment analysis and problem recognition
- Second meeting (12/10/16): Problem setting and requirements analysis
- Third meeting (14/12/16): Design of the solution

In the following chapters, detailed insights from each meeting will be presented and the process that led to the final outcome will be clear for the reader.

By the end of this chapter, the reader should have a clear understanding about the background of the present research, the objectives and the methodologies that have been used to pursue them. Following, one chapter will be dedicated for the discussion of each research question. For each research question, sample data and procedures will be deeply explained. Furthermore, results and insights will be reported for each research question.

CHAPTER 5 - UNDERSTANDING DETERMINANTS OF CREDIT RATING

In the previous chapter, research questions have been widely discussed and the research framework has been introduces. The first research question aims at understanding what are the key determinants of credit rating and at investigating the relationship between credit scoring models and credit ratings in the credit rating process made by banks and other financial institutions. R0 has been formulated as follows:

RQ0: *"Are credit scoring models consistent with credit rating ones? How much is the credit scoring's weight in the determination of the final credit rating"*

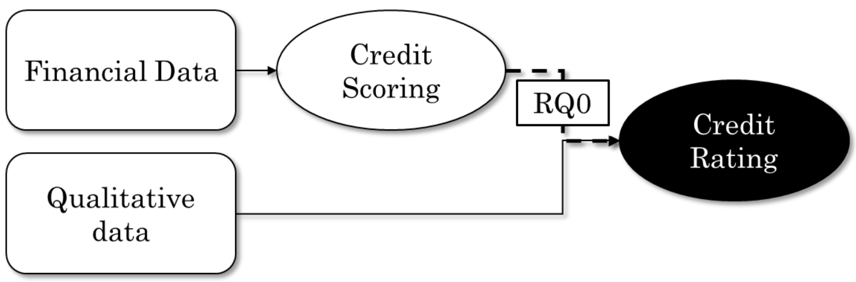

Figure 5.1 Visual representation of RQ0

Thus, the objective of the first research question is twofold: understanding whether the selected credit scoring models are consistent with the credit rating produced by BPER BANCA or not and determining how much weight the financial dimension accounts for in the BPER rating.

Conclusions to this research questions can follow two different scenarios:

1. A strong correlation between credit scoring models and BPER Banca credit rating is found. This would lead to the conclusion that credit scoring models are a significant tool to evaluate the credit risk of a company and, so, they would be integrated as a "corner-stone" of the new supply-chain oriented creditworthiness framework for the financial dimension;
2. No significant correlation between credit scoring models and BPER rating is found. Thus, this would open the way to further studies and investigation since this would go against most of the academic literature in this field of study.

5.1 Research Strategy and Method

This paragraph illustrates the methodology and structure used to carry out our research. Our work presents the following structure:

- Paragraph 5.2 clarifies the sampling approach and the firm qualification, a set of criteria that companies have to meet in order to be included in the sample. Then, the data collection method is proposed.
- Paragraph 5.3 clarifies the outcomes of the Spearman's correlation test between the BPER BANCA rating and the selected scoring models: Z-Score (Altman, 1968), Z'-Score (Altman, 1993), Z"-Score (Altman, Hartzell and Peck, 1995), O-Score (Ohlson, 1980) and Zmijewski (1984). This statistical test assesses how well the relationship between two variables can be described using a monotonic function. Thus, in our case it is used to understand if credit scoring models are consistent with the BPER BANCA rating.
- Paragraph 5.4 exemplifies the one-way ANOVA test, which is a technique that can be used to compare means of a continuous variable among three or

more groups. In our research, we have compared the means of the BPER BANCA Rating for each of the groups identified by the "most-consistent" credit scoring model identified in the paragraph 4.1.3.

5.2 The Dataset

Since this research question has been addresses to be answered only with statistical models, the data sampling played a significant role in the work. As already introduced in the previous chapter, for this RQ only financial and credit rating data are required. Thus, data sample in this situation is constituted by companies taken from BPER Banca (credit rating) and matched with AIDA to retrieve financial statements data. According with the model introduced in Chapter 4, the visual sample used in this research questions is the following grey area:

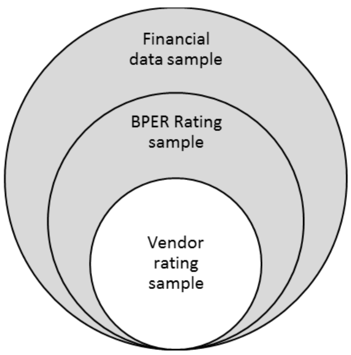

Figure 5.2 RQ0 sample

Firstly, the starting sample was made of 1006 companies that are populated with BPER Banca credit rating. This first sample is composed by small and medium Italian enterprises. Figure 5.3 shows the distribution of BPER Banca credit rating in the sample. Values ranges from 1 to 12 where the less the value, the higher the credit rating. According to guidelines provided by BPER Banca, companies with rating 1-4 are considered "*Good*", 4-6 as "Critical", from 6-11 as "Under observation" and 12 as "Defaulted".

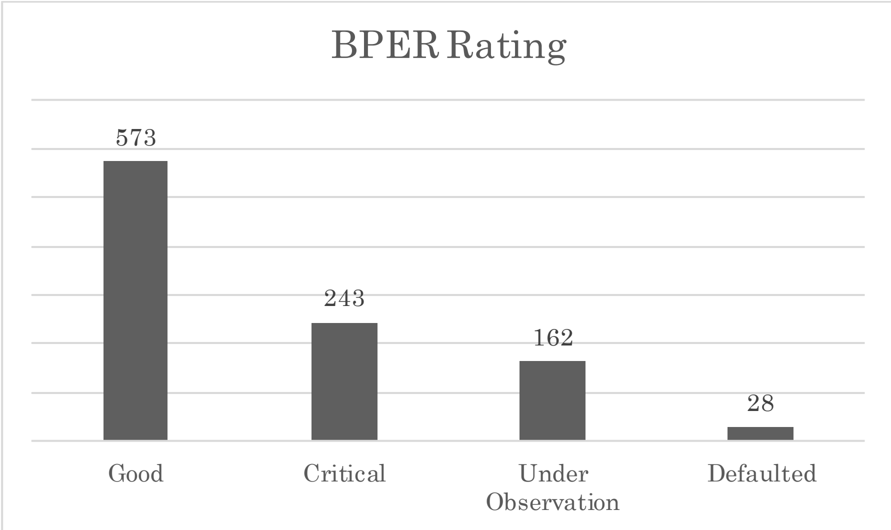

Figure 5.3 Rating-based sample distribution in the first dataset

Once the starting sample with credit rating data is constituted, the goal is to have a complete dataset of companies for which it is possible to calculate the ratios of the selected credit scoring models. In particular, for each firm we calculate the 2015 credit score of the following models: *Z-Score (Altman, 1968), Z'-Score (Altman, 1993), Z"-Score (Altman, Hartzell and Peck, 1995), O-Score (Ohlson, 1980) and Zmijewski (1984).* In Table 5.1 it is presented a summary of the financial ratios that has been calculated for the computation of credit scores.

Variables	Z-Score	Z'-Score	Z"-Score	O-Score	Zmijewski
X_1	$\frac{Working\ capital}{Total\ assets}$	$\frac{Working\ capital}{Total\ assets}$	$\frac{Working\ capital}{Total\ assets}$	$\log(Total\ assets)$	$\frac{Net\ income}{Total\ assets}$
X_2	$\frac{Retained\ earnings}{Total\ assets}$	$\frac{Retained\ earnings}{Total\ assets}$	$\frac{Retained\ earnings}{Total\ assets}$	$\frac{Total\ liabilities}{Total\ assets}$	$\frac{Total\ liabilities}{Total\ assets}$
X_3	$\frac{EBIT}{Total\ assets}$	$\frac{EBIT}{Total\ assets}$	$\frac{EBIT}{Total\ assets}$	$\frac{Working\ capital}{Total\ assets}$	$\frac{Current\ liabilities}{Current\ assets}$
X_4	$\frac{Market\ value\ equity}{Book\ value\ of\ total\ debt}$	$\frac{Book\ value\ equity}{Book\ value\ of\ total\ debt}$	$\frac{Book\ value\ equity}{Book\ value\ of\ total\ debt}$	$\frac{Current\ liabilities}{Current\ assets}$	-
X_5	$\frac{\boldsymbol{Sales}}{\boldsymbol{Total\ assets}}$	$\frac{Sales}{Total\ assets}$	-	1 if liabilities > assets, otherwise 0.	-
X_6	-	-	-	$\frac{Net\ income}{Total\ assets}$	-
X_7	-	-	-	$\frac{Net\ income + D\&A - Dev.}{Total\ assets}$	-
X_8				1 if profit < 0 for the last two years, otherwise 0.	
X_9				$\frac{Net\ income_t - Net\ income_{t-1}}{Net\ income_t + Net\ income_{t-1}}$	

Table 5.1 Variables of main credit scoring models found in literature

Afterward, the data-cleaning phase was performed through the following steps:

i. In order to have the most complete sample possible, companies that lacked of at least one necessary measure have been excluded from the analysis.
ii. Once the calculation of ratios is completed, companies that showed some unrealistic values have been omitted from the analysis (i.e. those firms which had the denominator of one of the variables equal to zero).
iii. Some of extremely well-performing firms and border-line firms may result in outliers and excluded in the analysis after the trimming phase.

After this filtering process, the resulting sample was reduced of 806 companies, distributed by BPER Banca credit rating as in the following chart. Even if this trimming phase has reduced the overall sample size, the distribution has not changed and, furthermore, this action has guaranteed the completeness of data that increased effectiveness of statistical models.

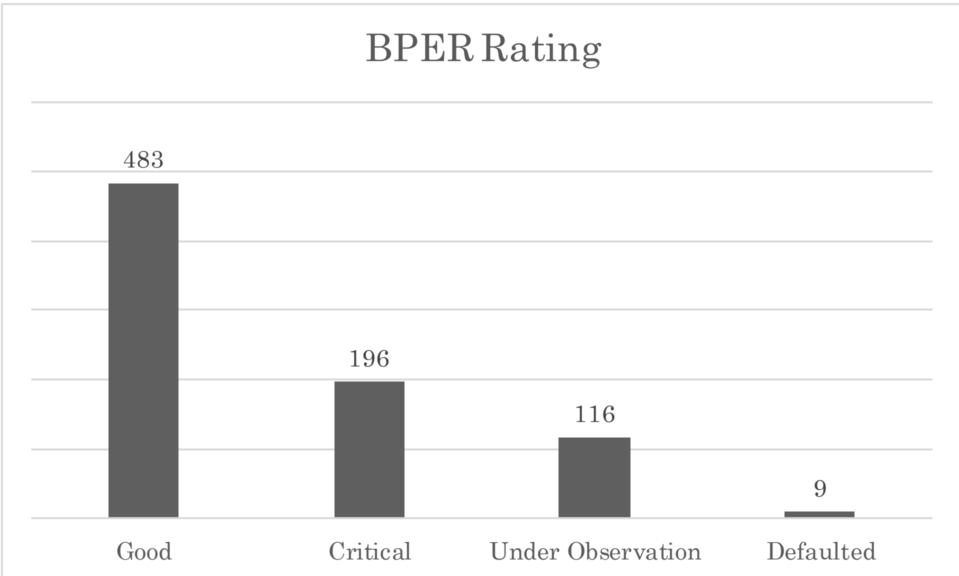

Figure 5.4 Distribution of companies based on the BPER rating in the final dataset

5.3 Correlation matrix

This first methodology has the goal of understanding the relationship between two key dimensions in the model: credit scoring and credit rating. The rationale behind this analysis is the desire to throw light on the determinants of credit rating. In literature, it is common knowledge that credit scoring plays the major role in the determination of the final rating but empirical analysis are not common.

The first target is about understanding whether BPER BANCA credit rating is consistent with all credit scoring models or not. The main advantage of using this methodology is that it allows to compare all the credit scoring models simultaneously with the credit rating. Furthermore, this will allow to discover which of the credit scoring models under analysis have the higher correlation coefficient with the rating developed by BPER BANCA. Identifying the credit scoring model that is the "best-fitting" with the contingencies of the Italian context, is a key-step to the formulation of the innovative supply-chain oriented creditworthiness framework. Furthermore, this allows to have a clearer idea about how the BPER BANCA rating is made since in the data collection process, only the synthetic credit rating evaluation has been retrieved. In fact, if we find out that no consistency exists between the BPER BANCA rating and the credit scoring we would end up with two different assumption: on one hand that credit rating models are not useful to understand the rating that are actually developed by banks and, on the other one, that the financial perspective is not the predominant part of them (which we know it is from the literature review). Thus, we decided to perform the Spearman's rank-order correlation.

This test calculates a coefficient, r_s or ρ (pronounced "rho"), which is a measure of the strength and direction of the association/relationship between two continuous or ordinal variables. For example, a Spearman's correlation is used to determine whether there is an association between exam performance and time spent revising (i.e., where exam performance and time spent revising are both measured on a continuous scale). In our case, what we want to test are the correlation between the BPER BANCA rating and each of the outputs of the considered credit scoring models. The Spearman's correlation test has three main assumptions (Laerd):

- **Assumption #1:** The variables must be measured on a continuous and/or ordinal scale;
- **Assumption #2:** The variables must represent paired observations. For example, with 30 participants in the study, this means that there would be 30 paired observations;
- **Assumption #3:** There needs to be a monotonic relationship between the two variables. This assumption can be checked by plotting a scatterplot and visually inspecting the graph.

The hypothesis for this test are the following:

H_0: $\rho = 0$, the correlation coefficient is equal to zero in the population.

H1: $\rho \neq 0$, *the correlation coefficient is not equal to zero in the population.*

Thus, the first thing to do is to check if our data respect the previously listed assumptions. The first assumption is easily verifiable. The credit scoring models' outputs are measured on a continuous scale, while the BPER BANCA rating on an ordinal one (values go from 1 to 12). Even the second assumption is easily satisfied by our data. In fact, the 806 companies included in the dataset have values for each of the considered variables. The last thing to do before running the Spearman's rank-order correlation test is to check if the third assumption is satisfied, too. Using IBM SPSS®, several scatterplots have been designed to determine if a monotonic relationship does exist between variables. In this chapter, it is reported only the plot that investigate the relationship between Altman Z" score and the BPER Banca credit rating.

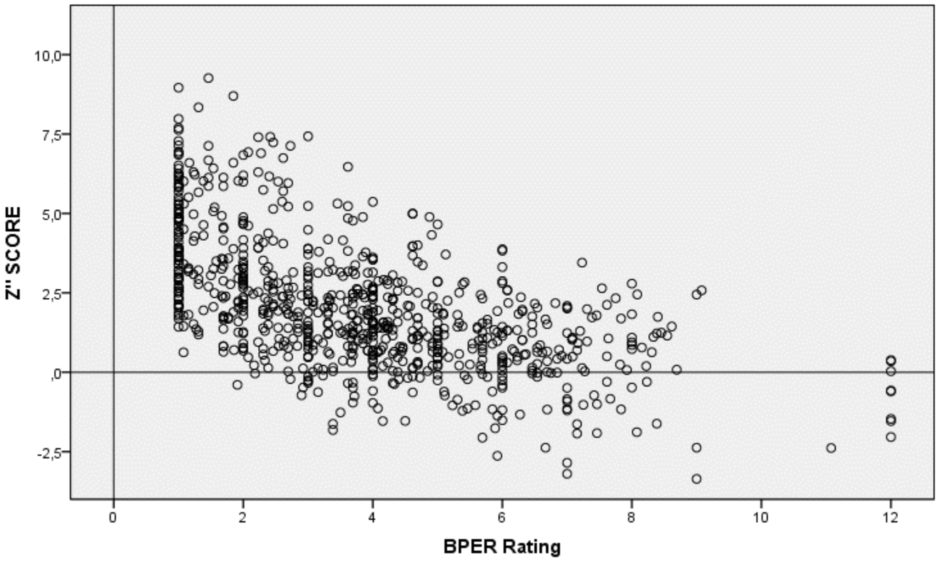

Figure 5.5 Monotonic relationship between Z''-Score and BPER Rating

In this case, the scatterplot suggests that there is a monotonic negative relationship between the Z" Score developed by Altman and the BPER BANCA rating.

5.3.1 Spearman's correlation procedure

Since all the assumption have been correctly verified, we can perform the test. The first step in interpreting the results is to understand the Spearman's rank-order correlation coefficient value (rs or ρ), which is a measure of the strength and direction of the association between your two variables. The correlation coefficient can assume values that range from +1 to -1, which indicates a perfect positive (+1) or negative (-1) association of ranks. A correlation coefficient of zero (0) indicates no association between the ranks, while the closer the correlation coefficient is to +1 or -1, the stronger the association between the ranks. The second step in interpreting the results is to determine whether the Spearman's rank-order correlation coefficient value is statistically significant. This will allow to determine whether to accept or reject the null hypothesis. With $\alpha = 0.05$ (i.e., $p < .05$), achieving a statistically significant Spearman rank-order correlation means that there is less than a 5% chance that the strength of the relationship found (the correlation coefficient) happened by chance if the null hypothesis were true.

		BPER Rating	Z Score	Z' Score	Z" Score	Zmijewski Score	O Score
BPER Rating	Correlation Coefficent	1	-0,545	-0,496	-0,605	-0,437	0,392
	Sign.		0	0	0	0	0
	N	804	804	804	804	804	804

Table 5.2 Spearman's non-parametric correlation table

From the table above, we can notice that all the scoring models have a satisfactory level of correlation with the BPER BANCA rating. The correlation's values have the correct sign for each of the credit scoring models. In fact, as the BPER BANCA rating decreases: on one side the Z-Score, the Z'-Score and the Z"-Score increase (negative correlation), and, on the other one, the O-Score and the Zmijewki score decrease (positive correlation). In particular, there is a strong negative correlation between the Z" Score developed by Altman and the BPER BANCA rating (r_s = -.605 and ρ < .0005). Thus, we can say that there is a significant relationship between the Z" Score and the BPER BANCA rating, so we can reject the null hypothesis and accept the alternative one.

5.3.2 Results

The application of this first methodology allows to start drawing some conclusions about the RQ0. The first insight is about the consistency that all credit-scoring models show with the BPER Banca rating. Values of correlation coefficients are high enough to meet initial expectations. Among all credit scoring models, *Altman Z" Score* results to be the most correlated with the credit rating (r_s = -.605). Overall correlation values are very satisfactory, as they demonstrate a high degree of correlation between credit scoring and credit rating.

From literature, it is common knowledge that credit scoring models take into account almost only financial variables, while credit rating is a more complex model that considers also qualitative aspects (i.e. enterprise strategy, macroeconomic environment…). However, it is clear that the financial perspective is the most relevant one since credit scoring models developed only with financial variables have a good correlation value with the BPER Banca rating.

In the end, we can state that the “best-fitting” credit scoring model for the BPER Banca rating is the Z”-Score model developed by Altman. This result is not surprising because this model was built for small and medium companies which represents the main part of our sample. From this point on, Altman Z” Score has been taken as reference for credit scoring models also for the following analysis.

5.4 One-Way ANOVA

ANOVA is one of the most popular statistical techniques for studies that aim to investigate differences between groups. Once items are classified into separated and independent groups, ANOVA provides insights about how some common dimensions vary between them. This technique differs from Student’s t-test because ANOVA allows sample split in three or more groups while Student’s t-test compare values only between two groups. For example, a one-way ANOVA is used to determine whether exam performance differed based on test anxiety levels amongst students (i.e., your dependent variable would be "exam performance", measured from 0-100, and your independent variable would be "test anxiety level", which has three groups: "low-stressed students", "moderately-stressed students" and "highly-stressed students"). In our case, what we want to determine is if BPER Banca credit rating is significantly different in each of the groups identified by the Z”-Score of Altman. If this statement is meet, we will have a further and more reliable proof of the consistency between the BPER BANCA rating and Z”-Score. The application of ANOVA implies that companies must be divided into clusters. This requirement has been addressed following Altman’s guidelines. The figure 5.6 shows how the clusters are formed according to the value that companies have obtained in the computation of the Z”-Score.

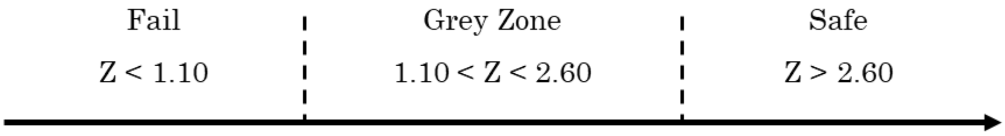

Figure 5.6 Risk-based cluster division suggested by Altman's Z''-Score

Companies with a *Z"-Score* lower than 1.10 are considered as "*Fail*" which indicates firms with a high probability of default in the considered period. On the other hand, if a company has a Z"-Score higher than 2.60, it is considered as "*Safe*", looking only at financial ratios. In the middle, there is the so-called "*Grey Zone*". Companies fall in this group because they cannot be considered neither "Safe" or "Fail". However, Altman suggests that this kind of companies have a good chance of going bankruptcy within the next two years of operations.

In order to run a one-way ANOVA, there are six assumptions that need to be met. The first three assumptions relate to the study design, whilst the second three assumptions relate to how good data fits the one-way ANOVA model. These assumptions are:

- **Assumption #1:** There is one dependent variable that is measured at the continuous level;
- **Assumption #2:** There is one independent variable that consists of two or more categorical, independent groups;
- **Assumption #3:** There is independence of observations, which means that there is no relationship between the observations in each group of the independent variable or between the groups themselves;
- **Assumption #4:** There should be no significant outliers in the groups of your independent variable in terms of the dependent variable;
- **Assumption #5:** The dependent variable should be approximately normally distributed for each group of the independent variable;
- **Assumption #6:** There should be homogeneity of variance.

It is important to remember that when a one-way ANOVA is run, the main aim is to determine whether the group means are different in the population. The hypothesis for this text are the following:

H0: all group population means are equal (i.e., $\mu 1 = \mu 2 = \mu 3 = \ldots = \mu k$)

H1: at least one group population mean is different (i.e., they are not all equal)

Where:

- μ = population mean;
- k = number of groups.

Referring to our case, the first three assumptions are satisfied. In fact, our dependent variable is the BPER BANCA rating and it is measured in a continuous way. The independent variable consists in the three groups identified by Altman through the Z"-Score (Safe, Grey Zone and Fail). In the end, there is independence of observations since sampling of one observation does not affect the choice of the second observation. The other three assumptions have been tested in a statistical way using IBM SPSS®.

Detecting outliers: The Tukey's method

The Assumption #4 states that we need to identify and exclude from the analysis the scores that are unusual in any group of the independent variable, either if their value is extremely small or large compared to the other scores. These scores are called outliers and they can have a large negative effect on your results because they can exert a considerable influence (i.e., change) on the mean and standard deviation for that group, which can affect the statistical test results. Outliers may cause a negative and misleading effect on data analyses and several outliers trimming methods have been established by scholars (Lehmann and Romano 2006). Explaining them goes beyond the aim of this dissertation, so we will give only a particular emphasis on the chosen method – i.e. the Tukey's (1977) method – and the reasons behind this choice. The Tukey's method is based on quartiles. The application of the method is straight-forward and relies as above said on the lower quartile ($Q1$), upper quartile ($Q3$) and the distance among them: the so called Inter Quartile Range ($IQR = Q3 - Q1$). Tukey defines as outliers all the observations which fall outside the following range:

$$(Q1 - k * IQR; Q3 + k * IQR)$$

Tukey suggests setting k equal to 1.5 to avoid any possible and probable outliers. As already mentioned before, the purpose of the application of Tukey's method was to not consider in our statistical analyses the outliers of the sample. The results of the application of Tukey's method is showed in the following chart.

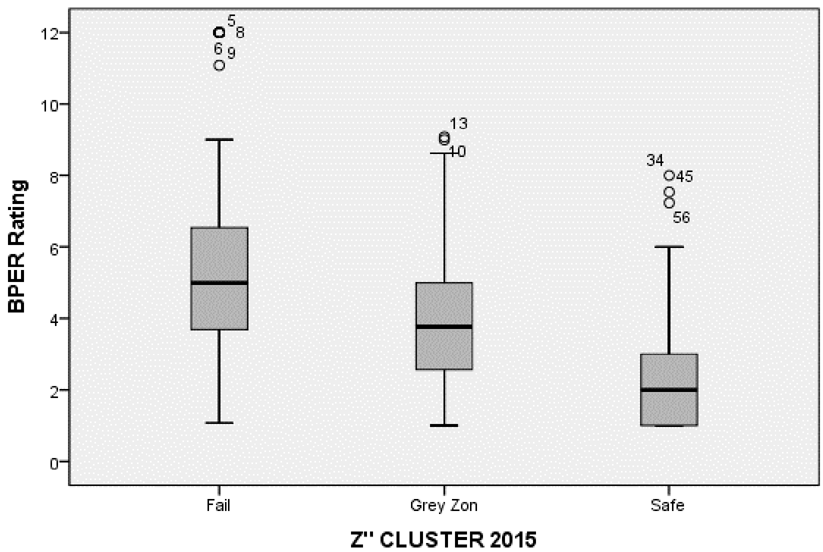

Figure 5.7 First application of the Tukey's method to detect outliers

Any data points that are more than 1.5 box-lengths from the edge of their boxes are classified by IBM SPSS® Statistics as *outliers* and are illustrated as circular dots. Any data points that are more than 3 box-lengths away from the edge of their box are classified as *extreme points* and are illustrated with an asterisk (*). Our sample has not extreme outliers and it has just a few points that can be considered as "soft" outliers. We decided to eliminate from the analysis those "soft outliers" for two main reasons: on one side, we want to achieve the more precise and reliable results as possible from the one-way ANOVA, and, on the other hand, the generous size of our sample allow us to ignore some companies. Thus, after running the Tuckey's method other four times and after eliminating all the outliers' companies, we can say that no more outliers are present in the data, as asserted by the inspection of the following boxplot chart.

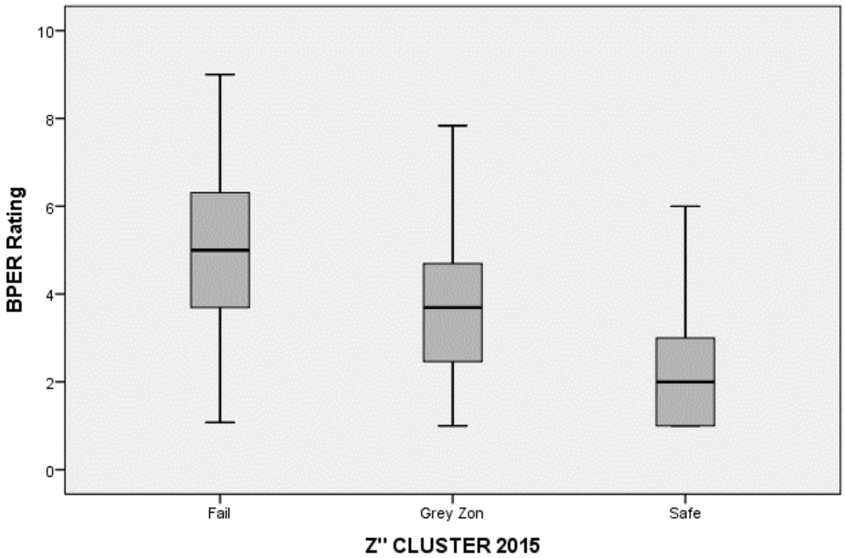

Figure 5.8 Last application of the Tukey's method

Thus, after this trimming phase 24 companies have been removed from the dataset (from 806 to 782 companies).

Detecting normality: Q-Q plots

The assumption #5 states that, for each group of the independent variable, the dependent variable should be approximately normally distributed. This assumption has been verified using a graphical method called Normal Q-Q Plots. A Normal Q-Q Plot is one of the best methods of assessing normality graphically. If data is normally distributed, the circular dots that represent the data points will be positioned approximately along the diagonal line in the Normal Q-Q Plot. In reality, there will be some variation from the line even when your data are approximately normally distributed. It is possible to see from the plots in Figure 5.8 that the points are approximately distributed along the diagonal line for each of the Z"-Score groups and so we can conclude that the difference scores are normally distributed (or at least approximately normally distributed, which is sufficient for the one-way ANOVA).

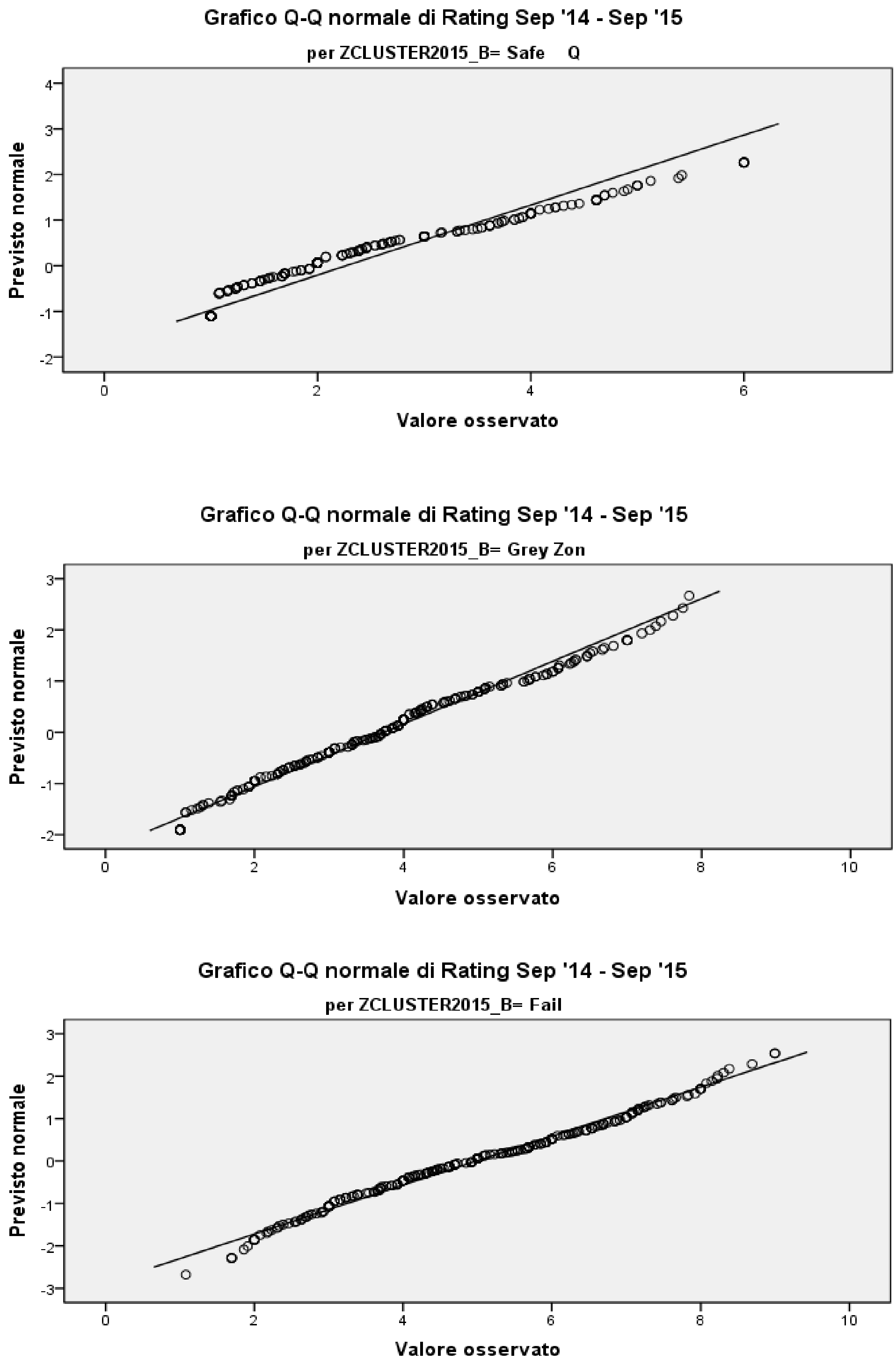

Figure 5.9 Normality plots for each of the Z''-Score clusters

Due to the observation of the previous Q-Q plots, we can state that the BPER BANCA rating score is normally distributed for fail, grey zone and safe groups.

Levene's test of homogeneity of variances

The assumption #6 of the one-way ANOVA assumes that the population variances of the dependent variable are equal for all groups of the independent variable. If the variances are unequal, this can affect the Type I error rate. The assumption of homogeneity of variances is tested using *Levene's* test of equality of variances, which is one way of determining whether the variances between groups for the dependent variable are equal. The result of this test is found in the Test of Homogeneity of Variances table, as highlighted below:

Levene's test	gl1	gl2	Sign.
12,470	2	779	**,120**

Table 5.3 Levene's Test of Homogeneity of Variances

The important column of the table above is the "Sig." column, which presents the significance value (i.e., p-value) of the test. If *Levene*'s test is not statistically significant (i.e., $p > .05$), you have equal variances and you have not violated the assumption of homogeneity of variances. In our case, we can state that there is homogeneity of variances, as assessed by *Levene*'s test for equality of variances ($p = .120$).

5.4.1 Results

Once all the assumptions of the one-way ANOVA are met, the actual ANOVA procedure can be run. The output provided by IBM SPSS is extensive and it goes beyond the focus of the present research. Thus, only a portion of the overall output is reported and discussed. First section of the ANOVA results are *descriptive statistics*. This table report descriptive values about data and they are presented for each cluster (*Fail, Grey zone* and *Safe*).

	N	Mean	Std. Deviation	Std. Error	95% Confidence Interval for Mean Lower Bound	Upper Bound	Minimum	Maximum
Fail	267	4,98	1,73	0,11	4,77	5,19	1,08	9
Grey Zone	262	3,73	1,64	0,1	3,53	3,93	1	7,83
Safe	253	2,27	1,3	0,08	2,11	2,43	1	6
Total	**782**	**3,69**	**1,92**	**0,07**	**3,55**	**3,82**	**1,00**	**9,00**

Table 5.4 Descriptive statistics of the One-Way ANOVA

From this table, it is possible to see that the average credit rating value ("mean") differs from one cluster to another. BPER Banca credit rating improves from Fail (4.98), to Grey Zone (3.73), to Safe (2.27). The trend of credit rating for each Z"-Score group becomes obvious consulting the line graph (i.e., mean plot), as shown below.

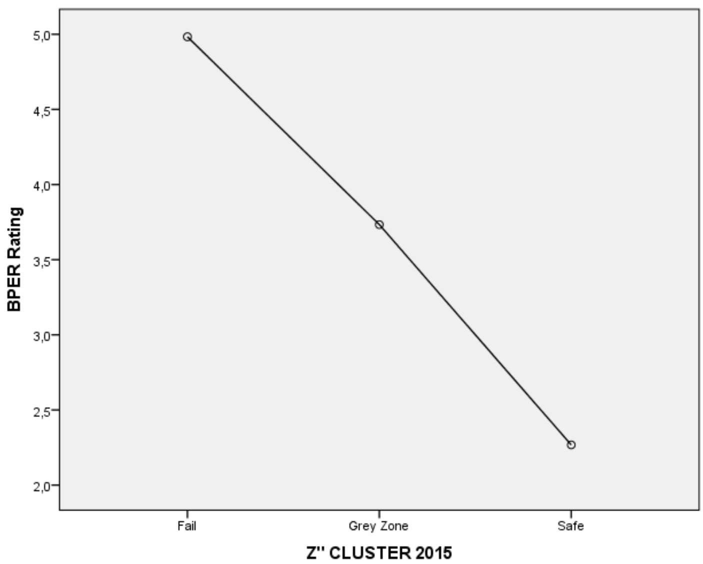

Figure 5.10 Mean Plot of the One-Way Anova

These first results suggest that the trend of BPER Banca credit rating is consistent with the risk-based classification suggested by credit scoring model. However, this is not enough to claim that those results have any statistical significance because the ANOVA results must be interpreted first. Following, the ANOVA results table is displayed providing an immediate output about the result of the test.

	Sum of squares	df	Mean square	F	Sign.
Between Groups	959	2	479	194	0,00
Within Groups	1927	779	2		
Total	**2885**	**781**			

Table 5.5 One-Way Anova results

The most important part of the table above is the "*Sig.*" column on the right-end that contains the statistical significance value (i.e., p-value) of the test found in the "Sig." column as highlighted in the table above. The lower the p-value, the higher the statistical significance of the test. In other words, p-value represents the probability that the differences in mean values found in the samples has been obtained by chance and, in the actual population, this difference is not significant. If $p > .05$, there is not statistically significant differences between the group means. In our case, the BPER Banca rating is statistically significantly different for different levels of the Z"-Score developed by Altman, $F(2,779) = 193{,}868$, $p < .0005$.

Once the significance level has confirmed that means of each group are not all equals, it is interesting to perform every possible pairwise comparisons. To do so, running a *post-hoc test* is recommended. This is a test that analyzes punctual differences between groups, in every possible group comparisons. The Tukey's post-hoc test is a good (Westfall et al., 2011) and recommended (Kirk, 2013) test for this purpose when the assumption of homogeneity of variances is not violated (and all other assumptions of the one-way ANOVA are met). This test is useful because it not only provides the statistical significance level (i.e., p-value) for each pairwise comparison, but it also supplies confidence intervals (aka Tukey's intervals) for the mean difference for each comparison. The results from the Tukey post hoc test are presented in the following table.

(I) Z"-Cluster	(J) Z"-Cluster	Mean Difference (I-J)	Std. Error	Sign.	95% Confidence Interval for Mean Lower Bound	Upper bound
Fail	**Grey Zone**	1,25	0,137	0,00	0,93	1,57
	Safe	2,72	0,138	0,00	2,39	3,04
Grey Zone	**Fail**	-1,25	0,137	0,00	-1,57	-0,93
	Safe	1,47	0,139	0,00	1,14	1,79
Safe	**Fail**	-2,72	0,138	0,00	-3,04	-2,39
	Grey Zone	-1,47	0,139	0,00	-1,79	-1,14

Table 5.6 Tukey Post Hoc Test

Table 5.6 shows one more time that the BPER BANCA rating is different between the Z”-Score groups and that the difference is statistically significant (Sign. ≈ 0).

5.5 Conclusions

This chapter has widely illustrated how the statistical methodology has responded to the first research question. This introductory question represented the foundation for the development of an innovative credit rating framework. In fact, a better understanding of the AS-IS situation is needed.

The combined use of statistical techniques has supported the discussion and provided the following insights.

- From Spearman’s correlation, the main insights are that all the credit scoring models under analysis show a concordant behavior with the credit rating provided by BPER Banca. Furthermore, the conclusion is that the high correlation coefficient (-0.6) is a proof that credit scoring plays a relevant role in the determination of final credit scoring. A further insight from the application of this methodology is about the comparison between different credit scoring models under analysis. Among all of them, Altman’s Z” Score results to be the credit scoring model with the highest correlation with BPER’s credit rating. This is a further confirmation that Z” Score was designed by Altman in order to fit better for non-manufacturing industries and emerging markets environments. Since the sample was almost free of manufacturing companies, this result confirms the hypothesis of Altman’s Z” score.
- From the One-way ANOVA, it was possible to analyze how the BPER credit rating differs between clusters suggested by Altman’s model. The first insight is that a statistically significant difference does exists between high-risk companies and low-risk companies according to Altman” cut-off. Furthermore, this difference shows a monotone regular trend as the credit

rating is significantly worse for companies with high-risk profile. In other words, companies that Altman's Z" model classifies as *high-risk profile* has an average BPER credit rating that is significantly higher than the other two groups. The behavior of the two dimensions is concordant.

This research questions aimed at providing insights about how financial institutions determine the credit rating in the AS-IS scenario. Furthermore, the understanding of determinants of credit rating was a crucial step towards one of the goal of this research: the creation of a supply chain-oriented creditworthiness model.

In the following chapter, the second research question will be introduced. The focus will be on the candidate to be included into creditworthiness assessment model: vendor rating data.

CHAPTER 6 – INFORMATIVE VALUE OF VENDOR RATING DATA

In the previous chapter, the first research question has been addressed. The previous research question investigates the relationship between credit scoring and credit rating. The second step of this research introduces the innovative dimension that is, now, missing to be included in credit rating models: vendor rating data. RQ1 can be formulated as follows:

RQ1: *"Would vendor rating data be redundant in a creditworthiness assessment model?"*

The common knowledge suggests that traditional credit rating models do not consider vendor rating in any form. However, every time a new input variable is added to an existing model, it is recommended to check that the potential informative gain is real. This research question has been included in the work because it is important to understand whether the addition of a new variable in a statistical model would bring additional information or not. Otherwise, there would be no need to introduce a redundant variable and its information would not be useful for the creation of a new and more effective credit rating model.

In order to do so, firstly, a vendor rating data must be compared with two existing variables in the model: credit scoring models and credit rating. These comparison is aimed to check if those two variables already "explain" the variation of operative performance of a company. The first step will be to check if vendor rating information are already included in credit scoring models, so in the financial dimension. Then, the comparison will be made with the BPER BANCA rating. In RQ0, we demonstrated that the BPER BANCA rating is mostly based on financial variable, but also more qualitative aspects are taken into account even if with a lower weight. Thus, it is important to figure out if vendor rating information are already explained in a more complex rating as the BPER BANCA one.

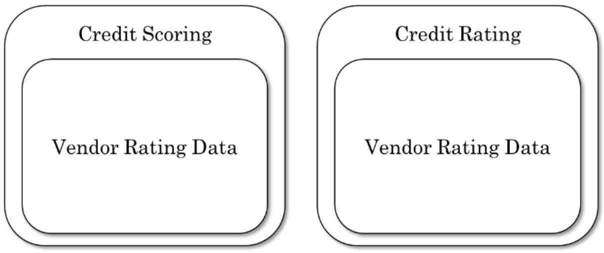

Figure 6.1 Visual representation of RQ1

6.1 Research Strategy and Method

This paragraph illustrates the methodology and structure used to carry out our research. Our work presents the following structure:

- Paragraph 6.2 clarifies the sampling approach and the firm qualification, a set of criteria that companies have to meet in order to be included in the sample. Then, the data collection method is proposed.
- Paragraph 6.3 is about understanding whether the information coming from vendor rating systems are already explained by financial ratios (In particular, respect to the Z"-Score of Altman). A first visual explanation will be proposed due to the utilization of a matrix. Then, an Independent T-Test will be used to statistically assess the insights that have come out from the visual inspection of the matrix.

- Paragraph 6.4 has the same structure of paragraph 6.3, but the view will be enlarged to the BPER BANCA rating with has a more complex structure than the Z"-Score since it takes into account also qualitative information. However, the final goal is the same: find out if vendor rating information are already included in the rating developed by BPER BANCA.

6.1 The Dataset

Here, the focus is on the vendor rating data retrieved from NIUMA. It is an innovative information provider that in 2004 created an e-procurement platform aimed to facilitate the relationship between customers and suppliers. As part of this platform, they created a section dedicated to the evaluation of suppliers by customers on six different dimensions: *quality, competency, flexibility, cost factors, promptness and punctuality*. Following, definitions of these factors is reported:

Vendor rating dimension	Definition
Quality	• The level of quality of products or services perceived by the customer. • If the product or service that has been provided is in line with customer's expectation. • The number of defected products on the total number of products that have been delivered.
Competency	• The level of support received by the customer in the delivery of the products. • The level of competence of the workers when delivering a service. • The supplier is in possession of specific vehicles that allow it to work in a superior way.
Flexibility	• The supplier accepts a modification of the order even at the latest moment. • The supplier is able to face unexpected accidents in a superior way.
Cost factors	• If the price provided is competitive in the market. • The value perceived by the customer is coherent respect to eventual investments.
Promptness	• If the supplier has respected the agreed and planned timing ensuring compliance with the scheduled work.
Punctuality	• If the products have been delivered on time. • In case of services, if the supplier has respected the contractual commitments on time.

Table 6.1 Definition of the vendor rating dimensions provided by NIUMA

As a pre-requisite for this analysis, a synthetic value for vendor rating is calculated starting from the single dimensions retrieved from Niuma dataset. The vendor rating values are all referred to the biennium between 2014 and 2015. In order to do so, each of the previously specified vendor rating dimension has been reported to a scale 1-10 and, finally a vendor rating score is created for each *i-th* company as follows:

$$VR_i = Quality_i + Competency_i + Flexibility_i + Cost_i + Promptness_i + Punctuality_i$$

The choice of giving the same weight to each of the vendor rating dimensions will be explained in the following chapter. However, this is one of the insights that came out from focus group sessions. Assigning a weight would be misleading for two different reasons: on one hand, different industries may perceive different importance to each dimension and, on the other hand, evaluation could come up from assigning weights to a dimension which is not objective, since it is influenced by personal considerations. As already explained in Chapter 4, in this research questions three types of data sample have been merged together to obtain a complete dataset. This operation required the integration of BPER Banca dataset, Niuma dataset and AIDA dataset. This three-way merge led to a final sample sample of 136 firms. Even if the sample size has significantly reduced from the original ones, the fact of having companies endowed with all three types of data at the same time is a positive upside of the analysis. Furthermore, the composition of this sample is satisfactory because it is suitable for the requirements of the tests that have been performed. The sample is composed by small and medium Italian enterprises. In our study, we followed the definition of SME given by the European Union Commission (2003) and described by Table below.

Size	**Staff Headcount**	**Turnover**	**Or**	**Balance Sheet**
Big	> 250	≥ € 50 million		≥ € 43 million
Medium	< 250	≤ € 50 million		≤ € 43 million
Small	< 50	≤ € 10 million		≤ € 10 million
Micro	< 10	≤ € 2 million		≤ € 2 million

Table 6.2 SME classification (European Union Commission, 2003)

In the final sample, companies are homogenously classified by size, as suggested by Figure 6.2.

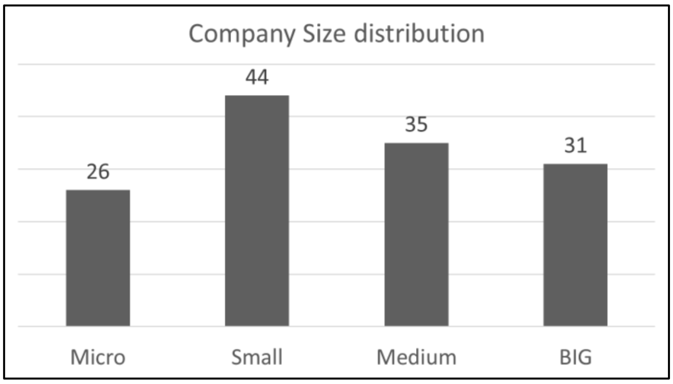

Figure 6.2 Size-based sample distribution

6.2 Vendor rating vs Credit Scoring

This first section of the paragraph focuses only on the relationship between vendor rating and the "best-fitting" credit scoring identified in RQ0 (Z"-Score). Thus, in the following paragraph only vendor rating and credit scoring data will be analyzed.

6.2.1 Z"- Score and Vendor Rating Matrix

Before performing structured statistical analysis, the first exploratory step is to use graphical tools. The first methodology that has been applied is to develop a matrix that compares vendor rating with existing variables. This matrix has the objective of understanding if there are any inconsistencies between the two ratings. Thus, if the vendor rating and the Z"-Score information are inconsistent, we will demonstrate the need of looking at both dimensions and not at the financial one in order to have a complete picture of the creditworthiness of a company. This first analysis does not have any statistical relevance, but it will help us to figure out if it is important to further investigate this issue or not.

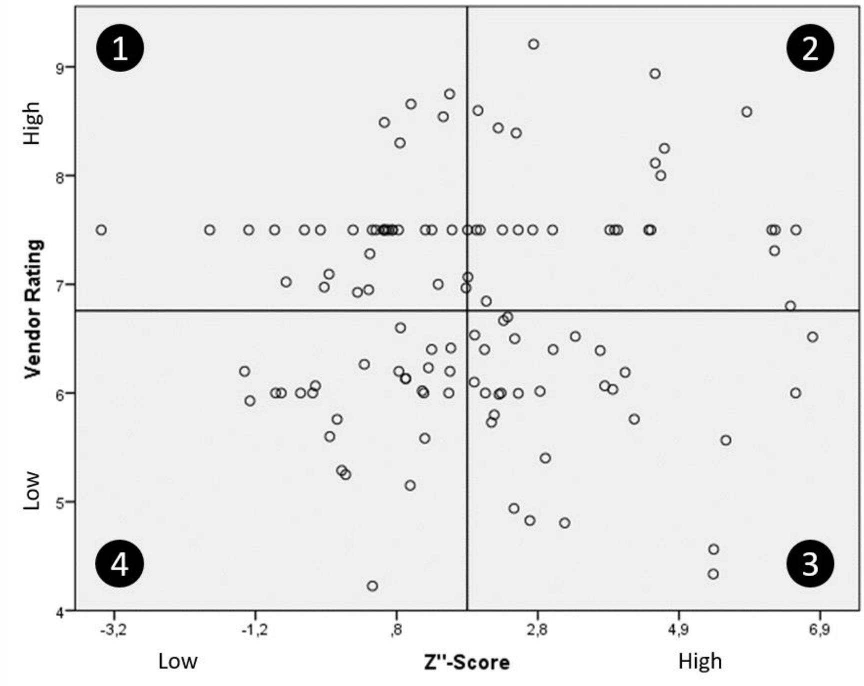

Figure 6.3 Matrix Vendor Rating vs Z''-Score

The matrix above represents how the 136 companies of the sample perform both in terms of the vendor rating score and of the Z”-Score. As regard of the quadrants division, the choice was to use the mean of the sample’s vendor rating score to divide in good and bad performing suppliers. Thus, the selected cut-off value is fixed at 6.67 which correspond to the mean of the sample. On the other hand, to divide good and bad companies in terms of the credit rating score, the cut-off identified by Altman is selected (1.85). Altman suggests that companies with a Z”-Score value greater than 1.85 are considered at low risk, on the other hand if that value is lower than 1.85 the companies have a high risk of default.

Thus, four different scenarios are defined:

Scenario	**Vendor Rating Score**	**Z"_Score**	**# of companies**	**% on total companies**
1	High	Low	36	26,5%
2	High	High	35	25,7%
3	Low	High	37	27,2%
4	Low	Low	28	20,6%

Table 6.3 Scenarios of the matrix Vendor Rating vs Z''-Score

The second and fourth scenarios are the easiest to be analyzed because vendor rating and Z”-Score are consistent and this means that vendor rating data do not provide a valuable distinct perspective in the assessment of companies' creditworthiness.

In the second scenario, there are well-performing companies in both of the considered dimensions. On the other hand, in the fourth scenario companies have poor scores in both of the dimension. These two scenarios accounts for the 46.32% of the cases. This means that the information coming from vendor rating score and the Z”-Score are consistent in less than the 50% of the cases. This is a first proof of the fact that there is the need of looking at both of the scorings to better depict the creditworthiness of a company.

In the remaining 53.68% of the cases, scenarios are not easily interpretable, so a further investigation is needed. In those scenarios, the vendor rating score is not concordant with the Z”-Score and therefore the overall situation of the suppliers belonging to these quadrants cannot be described looking only at financial or vendor rating data, but needs to be analyzed looking at both of them.

In the scenario 1 (26.47% of total companies), firms have a good vendor rating, but a poor Z”-Score. This situation could arise when considering a new-born firm or a micro company. An example for this scenario could be a company that works in the manufacturing industry and have created an innovative component for automotive engines. As far as vendor rating is concerned, this company is positively rated since it enters the market with innovative solutions and it is customer-oriented. On the financial side, since this company has a short life and small dimension, it has funded its growth with loans and its level of debt has increased. Furthermore, the level of profits is low in the short run due to high level of investments made to project the innovative component. In this case, there is the need to use both of the scoring measures to determine the company's creditworthiness. In fact, at the state-of-art banks would consider the company as at-risk due to its financial situation and would put a high interest level on their loans. This would certainly affect the profitability of the company compromising its growth. Thus, an integration of the two rating data sources can help to identify the firm's potentiality and to increase the credit concession to firms that worth it since banks would take decisions with more information.

In the same way third scenario (27.21% of total companies) describes companies that have a high Z"-Score but a low vendor rating. This scenario is more likely to happen with companies that are in the market since a lot of time. On one side, their financial performance is strong because the effect of their investments has already been absorbed and, on the other side, they could start to lower their operative performances due to different events (such as: the need to reduce costs, a new low cost companies enters the market, an industry or a worldwide crisis arise…). In this scenario, banks continue to concede credit to this kind of companies at a good interest level since their creditworthiness evaluation is mostly based on financial indicators that are static and reflect the past. Companies in the scenario 3 are considered by banks as "safer" than companies in the scenario 1. This could be considered true, but a lot of exceptions can arise. Thus, there is the need to consider both of the dimensions for each company to better assess their credit risk.

The considerations coming from this matrix state the importance of an integration between financial and vendor rating variables in an integrated supply chain oriented framework. In most of the cases, the single financial perspective is not enough to depict the creditworthiness of a company and incorrect decisions about the interest level of a loan can be taken. In order to have a better knowledge of the company and not to miss important information coming from the vendor rating system, a new and innovative view is needed.

6.2.2 Independent-samples T-Test

This paragraph introduces the second methodology that has been applied to answer to this research question. After performing the visual analysis, the goal of this paragraph is to statistically demonstrate the insight coming out of the previous methodology. The statistical model that has been chosen is the independent-samples Student t-test.

This test is used to determine if a difference does exist between the means of two independent groups on a continuous dependent variable. More specifically, it determines whether the difference between these two groups is statistically significant. In our case, the focus is on the vendor rating dimension and the objective is to understand whether it significantly differs between low-risk and high-risk companies. As previously specified, we use the cut-off point identified by Altman to determine if the Z”-Score of a company refers to a low or high credit risk. The application of Student t-test implies that companies must be divided into two groups before starting. This test requirement has been addressed following Altman’s cut-off guidelines. Altman suggests that companies with a Z”-Score value greater than 1.85 are considered at low risk, on the other hand if that value is lower than 1.85 the companies have a high risk of default. Thus, the two independent samples used in the test are as follows.

Z"-Score classification	# of Companies
HIGH RISK	64
LOW RISK	72
Grand Total	136

Table 6.4 Sample division by Altman's cut off

In order to run an independent-samples t-test, there are six assumptions that need to be considered. The first three assumptions relate to the choice of study design and the measurements that are chosen to make, whilst the second three assumptions relate to the characteristics of the data that are actually collected. These assumptions are:

- **Assumption #1:** One dependent variable is measured at the continuous level.
- **Assumption #2:** One independent variable consists of two categorical, independent groups (i.e., a dichotomous variable).
- **Assumption #3:** There is independence of observations, which means that there is no relationship between the observations in each group of the independent variable or between the groups themselves.

- **Assumption #4:** There should be no significant outliers in the two groups of your independent variable in terms of the dependent variable.
- **Assumption #5:** The dependent variable should be approximately normally distributed for each group of the independent variable.
- **Assumption #6:** There should be homogeneity of variances (i.e., the variance is equal in each group of your independent variable).

Assumptions #1,#2 and #3 can be easily checked. Vendor rating is the dependent variable and it is measured at a continuous level in a scale from 1 to 10. The independent factor is the Altman Z" score cut-off that divide the sample into two independent groups: low-risk vs high-risk companies. Furthermore, independence of observations can be assumed since there is no relationship between the participants in either of the groups. For the remaining hypothesis, some procedure must be performed and they will be described in the following paragraphs.

Detecting outliers: Tukey's Method

In order to check assumption #4, the Tukey method is again performed. The goal is to identify if the dependent variable (vendor rating dimensions) has outliers in each of the two groups identified from the Z"-Score. The way this test works has been already described in the previous research question.

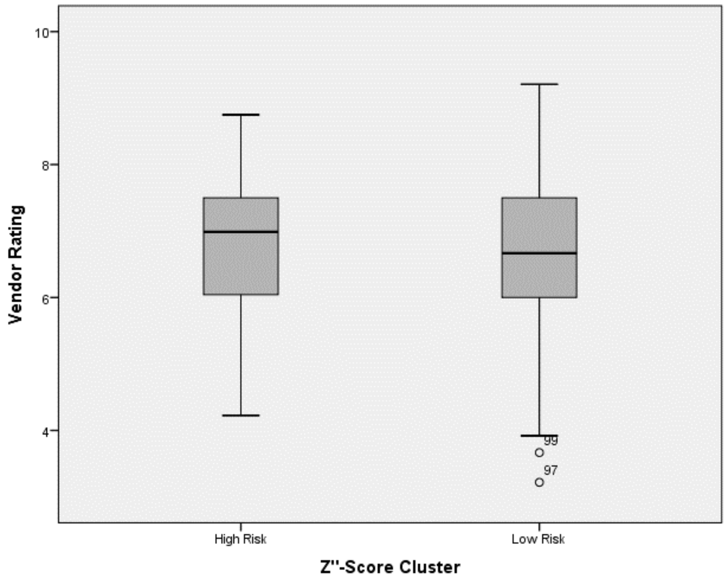

Table 6.5 First application of the Tukey method

In the sample, there are not *extreme outliers* (data points that are more than 3 box-lengths away from the edge of their box) but only two outliers are identified and excluded from the analysis. The second iteration of the test shows that no more outliers are present in the sample, so we can proceed with the analysis.

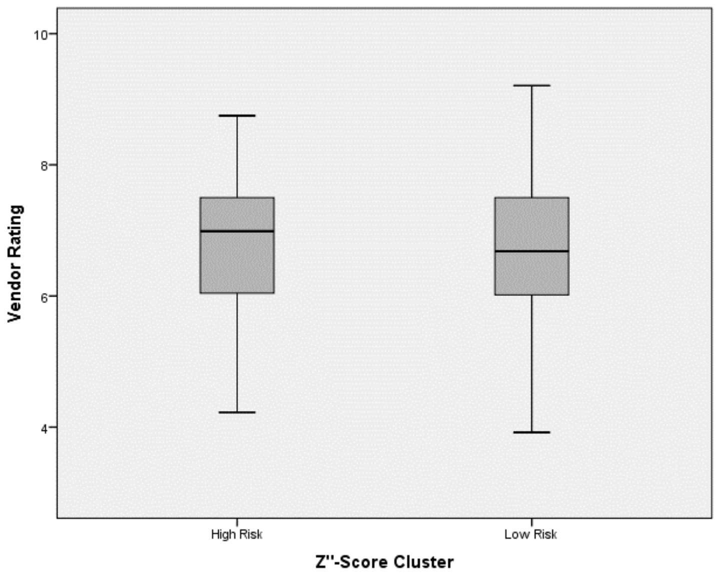

Table 6.6 Final application of the Tukey's method

Detecting normality: Shapiro-Wilk test

The Shapiro-Wilk test is meant to confirm whether a certain dependent variable is normally distributed, for each category of the independent variable, or not. Hence, there will be as many Shapiro-Wilk results as there are categories of the independent variable (in this case two: high-risk and low-risk).

The choice of using this test instead of a graphical inspection (Q-Q plots as RQ0) is due to the limited size of the sample. In fact, this test is the best choice when sample size is not too wide. The main output of this test is the following reported table with results. The "Sig." column provides indication about the distribution of the variable under analysis. If data are normally distributed (the assumption of normality is met), the significance level (value in "Sig." column) should be higher than 0.05.

	Z''-Score Cluster	Statistic	df	Sig.
Vendor Rating Score	High Risk	0,941	64	0,144
	Low Risk	0,969	70	0,075

Table 6.7 The Shapiro-Wilk test

We can state that the vendor rating score for each level of the Z”-Score is normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$).

Levene’s test of homogeneity of variances

This last hypothesis is not as strict as the previous ones. In fact, depending on the distribution of variances, a different statistic is calculated as results of the test. The optimal situation is that variances of dependent variable are homogeneous in both the two independent groups. Failure to adhere to this assumption (i.e., if variances are not homogeneous), generally increases the chance of making a Type I error. In other words, Levene's test checks whether the two samples came from populations with the homogeneity of variances.

IBM SPSS® automatically include Levene's Test for Equality of Variances inside the results of Student t-student. The results of this test are reported in the same table of the overall results, as reported in the Table 6.8.

		F	Sig.
Vendor Rating Score	**Equal variances assumed**	1,269	0,262
	Equal variances not assumed		

Table 6.8 Levene's test for equality of variances

To check whether the population variances are equal, you need to consult the "Sig." column located under the "Levene's Test for Equality of Variances" column. In our case, there is homogeneity of variances, as assessed by Levene's test for equality of variances (p = .262).

Results

The Group Statistics table below contains some useful descriptive statistics for your two groups – "Low-Risk" and "High-Risk" – which will help to get a "feel" for the data.

	Z"-Score Cluster	N	Mean	Std. Deviation	Std. Mean Error
Vendor Rating Score	**High Risk**	64	6,83	0,94	0,117
	Low Risk	70	6,79	1,11	0,132

Table 6.9 Descriptive statistics

Each row in the table above presents statistics on the dependent variable (Vendor Rating score), for the different categories of the independent variable (Z"-Score Cluster). Reported values include "mean", "standard deviation" and "standard mean error". A first takeaway of this table is that high-risk companies' average vendor rating (6.83) is higher than low-risk companies' average vendor rating (6.78). Logically speaking, low-risk companies should have better vendor ratings than high-risk ones. This means that generally the financial information classifies companies in a different way respect to the vendor rating score.

Getting to the most important table of all results, since the assumption of homogeneity of variances is met, we can interpret the results from the standard t-test that uses pooled variances in its calculations and requires no modification to the degrees of freedom.

		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval for Mean Lower	Upper
Vendor Rating Score	**Equal variances assumed**	0,24	132,0	0,810	0,043	0,178	-0,310	0,395
	Equal variances not assumed	0,24	132,3	0,808	0,043	0,177	-0,307	0,393

Table 6.10 T-Test for equality of means

In the table above, there are reported main results of the Student t-test. Vendor rating of high-risk companies is 0.043 points higher than the low-risk ones. However, this difference is not significant as the confidence interval (CI 95%) of this difference includes the value 0. Thus, we can notice that it is null the difference between high-risk companies and low-risk companies in terms of vendor rating performances. A further confirmation comes from the significance level of the t-test, reported in the column "Sig (2-tailed)". If Sig < 0.05, it means that the difference between means of the two groups is statistically significant. In this case, there is not a statistically significant difference in mean of the vendor rating score between low-risk and high-risk companies (p = 0.810).

This is another confirmation that financial variables are not able to explain the information coming from the vendor rating systems. It is important to specify that vendor rating variables are not meant to replace financial ones since it is widely recognized that the financial dimension is the most important one to assess credit risk. However, it is not possible to ignore the fact that vendor rating variables and financial ones give different perspectives of the current situation of a company. Therefore, a joint vision is required to have a more precise view of companies' creditworthiness.

6.3 Vendor rating vs Credit Rating

The second section of the chapter focus on the relationship between vendor rating and credit rating. Thus, in the following paragraphs only vendor rating data from Niuma and credit rating data from BPER Banca will be used.

6.3.1 Credit Rating and Vendor Rating Matrix

So far, it has been analyzed the relationship between vendor rating and credit scoring. The conclusion is that credit scoring model (Altman Z" Score) does not explain vendor rating variation.

Since we demonstrate that vendor rating information are missing in credit scoring models, now the focus is on the comparison between the vendor rating variable and the BPER Banca Rating. The process is the same: firstly, a graphical analysis will be performed and, then, a statistical one.

The BPER BANCA rating and vendor rating score matrix will give us important insights on the matter.

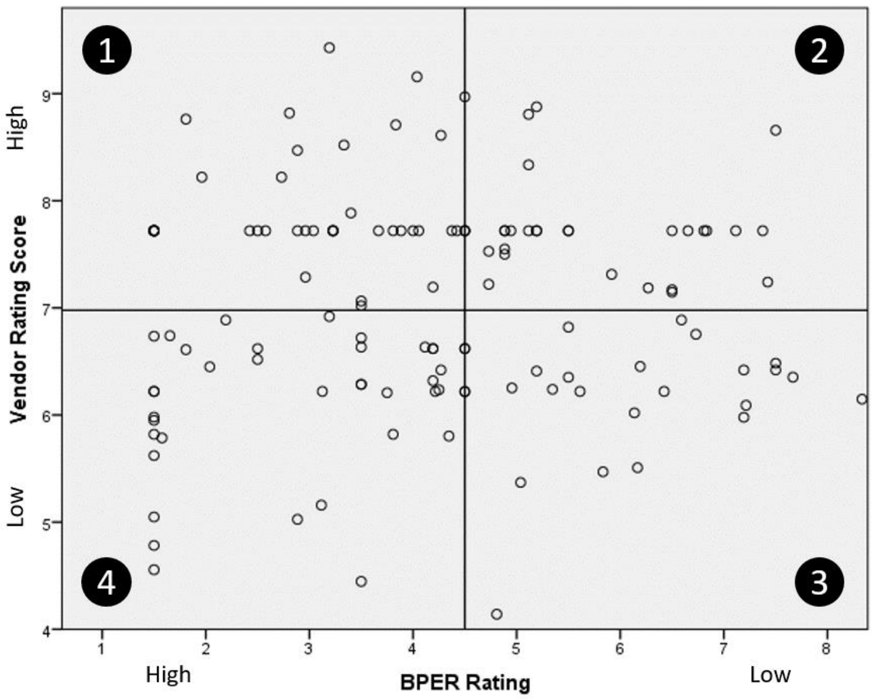

Figure 6.4 Matrix Vendor Rating vs BPER rating

As assessed by Figure 6.3, even this figure gives an immediate impact that the information coming from BPER Banca and NIUMA are discordant in most of the cases.

As regard of the quadrants division, the choice was to use the mean of the sample's vendor rating score to divide in good and bad performing suppliers. Thus, the selected cut-off value is set at 6.67 that is the mean of the sample.

Instead, the cut-off that divide into well-performing and bad companies in terms of credit rating has been set accordingly to the guidelines provided by BPER. In particular, BPER Banca considers "good" only companies that have a credit score lower than 4. Following, a table that provide an overview of the matrix.

Scenario	Vendor Rating Score	Z"_Score	# of companies	% on total companies
1	High	Low	38	27,9%
2	High	High	29	21,3%
3	Low	High	32	23,5%
4	Low	Low	37	27,2%

Table 6.11 Scenarios of the matrix Vendor Rating vs Z''-Score

In this matrix, the second and the fourth scenarios are the ones where the vendor rating and the credit rating are concordant. These two scenarios accounts for the 48.53% of the total number of companies. An improvement of this percentage respect to the first matrix is expected since the BPER Banca rating collects information from more dimensions (48.53% > 46.32%). However, the result is still unsatisfying because almost one company out of two has a situation in which the two dimensions are discordant. In the first scenario, companies are good in terms of the vendor rating, but poor in terms of the credit rating. In the third scenario, the opposite situation

As previously discussed, the picture in those cases is not clear at a first sight. The creditworthiness of those companies needs to be further investigated to discover why the two dimensions are giving opposite directions. Furthermore, this is a first proof that even a more complex rating model such as the BPER BANCA one is missing the information coming from the vendor rating perspective.

6.3.2 Independent-samples T-Test

In order to demonstrate the insights coming from the graphical analysis, a more structured statistical approach has been performed. As in the previous case, the independent-samples Student's t-test is chosen.

Firstly, the six assumptions of this test need to be checked. The dependent variable is the vendor rating and it measured at a continuous level. Differently from the other analysis, the sample is divided in two groups accordingly to the guidelines provided by BPER Banca: low-risk and high-risk. In particular, companies with credit rating lower than 4 are considered "safe". This is the categorical independent variable of the test. In the end, there is independence of observation due to how the dataset has been build. At this point, three out of six assumptions have been satisfied.

Detecting outliers: Tuckey's Method

The fourth assumption states that no outliers for each categorical group must be present in the sample. After a first run of the Tuckey's method, the following box-plots describe the data distribution.

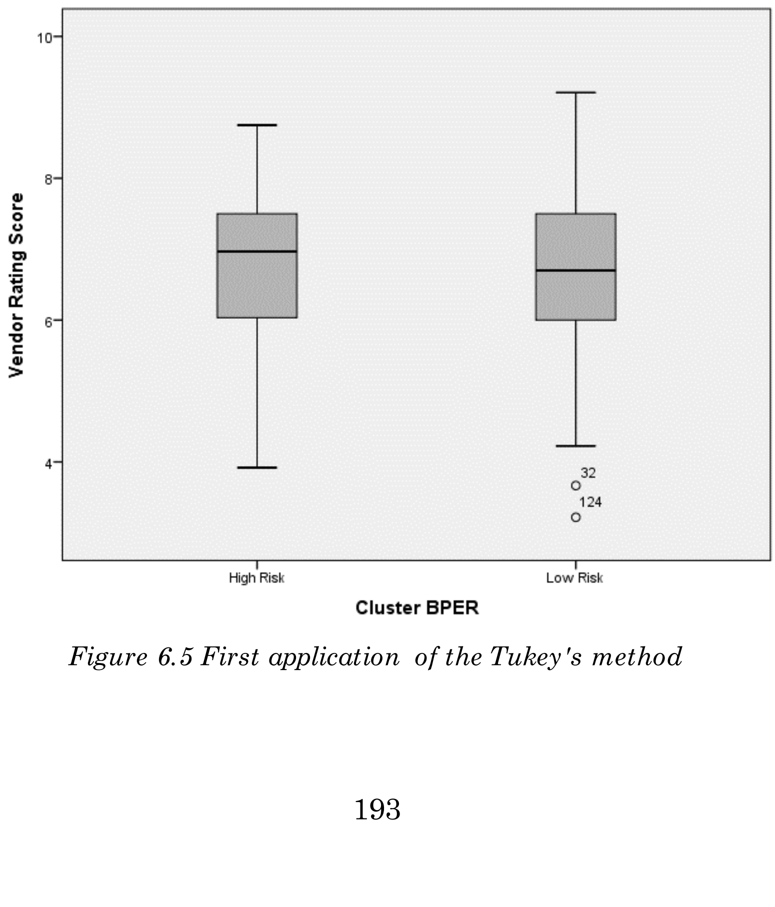

Figure 6.5 First application of the Tukey's method

There are two “soft” outliers in the sample that are excluded from the analysis. Once the test is run for the second time, no more outliers are found. The final sample is composed by 134 companies: 61 high risk and 73 low risk.

Detecting normality: Shapiro-Wilk test

In order to check the fifth assumption, the Shapiro-Wilk test is performed. In the table below, you can see that both of the "Sig." values are greater than .05 (they are .152 and .052), and therefore, the dependent variable, vendor rating score, is normally distributed for each level of the independent variable, BPER BANCA Cluster.

	Z"-Score Cluster	Statistic	df	Sig.
Vendor Rating Score	High Risk	0,940	61	0,152
	Low Risk	0,965	73	0,052

Table 6.12 Shapiro-Wilk test

Levene’s test of homogeneity of variances

The last assumption that need to be verified is the one of the homogeneity of variances. To check whether the population variances are equal, you need to consult the "Sig." column located under the "Levene's Test for Equality of Variances" column. In our case, the significance value is ".169". If the population variance of both groups is equal, this test will return a p-value greater than 0.05 (i.e., $p > .05$), indicating that we have met the assumption of homogeneity of variances.

		F	Sig.
Vendor Rating Score	**Equal variances assumed**	1,911	0,169
	Equal variances not assumed		

Table 6.13 Levene’s test of homogeneity of variances

Results

The Group Statistics table below contains some useful descriptive statistics for your two groups – "Low-Risk" and "High-Risk" – which will help to get a "feel" for the data.

	Z''-Score Cluster	N	Mean	Std. Deviation	Std. Mean Error
Vendor Rating Score	**High Risk**	61	6,82	0,94	0,120
	Low Risk	73	6,80	1,10	0,129

Table 6.14 Group Statistics

Each row in the table above presents statistics on the dependent variable (Vendor Rating score), for the different categories of the independent variable (BPER Cluster). Reported values include "mean", "standard deviation" and "standard mean error". A first takeaway of this table is that high-risk companies' average vendor rating (6.82) is slightly higher than low-risk companies' average vendor rating (6.80). Logically speaking, low-risk companies should have better vendor ratings than high-risk ones. This means that generally the financial information classifies companies in a different way respect to the vendor rating score.

Getting to the most important table of all results, since the assumption of homogeneity of variances is met, we can interpret the results from the standard t-test that uses pooled variances in its calculations and requires no modification to the degrees of freedom.

		t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval for Mean Lower	Upper
Vendor Rating Score	**Equal variances assumed**	0,11	132	0,914	0,194	0,179	-0,334	0,373
	Equal variances not assumed	0,11	132	0,912	0,194	0,176	-0,329	0,368

Table 6.15 T-Test equality of means

In the table above, there are reported main results of the Student t-test. Vendor rating of high-risk companies is 0.194 points higher than the low-risk ones. However, this difference is not significant as the confidence interval (CI

95%) of this difference includes the value 0. This means that there is the possibility that, in the original population, this difference is term of vendor rating performance between high-risk companies and low-risk companies is actually null. A further confirmation of it, is the significance level of the t-test, reported in the column "Sig (2-tailed)". If Sig < 0.05, it means that the difference between means of the two groups is statistically significant. In this case, there is not a statistically significant difference in mean of the vendor rating score between low-risk and high-risk companies ($p = 0.914$).

Now, it is possible to assert that also credit rating data are not able to explain any kind of vendor rating variation.

6.4 Conclusions

This chapter has widely illustrated how the statistical methodology has responded to the second research question. This question represented the first innovative contribution of this study. In fact, the focus is on vendor rating data that represent the real new dimension in credit rating models.

The combined use of statistical techniques has supported the discussion and provided the following insights.

- From *visual data analysis*, many insights can be derived. A first outcome is about the distribution that the sample follows among the four quadrants of the two matrixes (*vendor rating – credit scoring matrix, vendor rating – credit rating matrix*). The following considerations are valid both for the credit scoring matrix and the credit rating matrix since we already demonstrated that these two dimensions are strongly correlated in the first research questions. From this visual tool, it is easy to see that most of the points on the graph does not follow a linear trend. Instead, they are highly scattered around the graph and there are many point that are located where vendor rating and the second dimension are discordant. This is an extremely relevant conclusion for those companies in which vendor rating data and financial information show inconsistent behavior, in fact, vendor rating data could represent a different perspective that could dramatically change the creditworthiness evaluation by financial stakeholders.

- In *Student's t-tests*, it was possible to approach the research question with a statistical technique. First the sample was clustered into two groups: high-risk companies and low-risk companies. This classification has been done according to recommendations from Altman's Z" model and BPER Banca classification. The t-test helped to compare mean values of the vendor rating data between the two aforementioned clusters. In this way, it resulted that there is no significant difference regarding vendor rating between companies discriminated by Altman and BPER criteria. Thus, this is a further important confirmation of the fact that BPER and Altman are not enough to reflect operative performances and, thus, additional information are needed. This missing piece of information is represented by vendor rating data whose data are not currently explained in any way by existing variables.

In conclusion, all the methodologies that have been applied have confirmed that there is no correlation between vendor rating data and any other variables that is already included in the model. No correlation between vendor rating data and credit scoring data means that financial information cannot explain the variation of operative performance by themselves. Furthermore, the absence of correlation between vendor rating data and credit rating suggests that operative performances are not taken into account neither in the "qualitative information" that differentiate credit scoring from credit rating. Hence, this research question represents a big step forward to the final goal of this research. The informative content of vendor rating data is a potential that it is hidden and it is still not exploited by any other informative source in traditional creditworthiness models.

In the following chapter, the third research question will be introduced. Once it is demonstrated that vendor rating data represent a valid source of information, the scope is about defining how to integrate them inside a creditworthiness model and evaluating the effectiveness of this integration.

CHAPTER 7 – INTEGRATED SUPPLY-CHAIN ORIENTED CREDITWORTHINESS FRAMEWORK

The third research question of our study tries to answer in a comprehensive and complete way to the following question:

"Is it possible to develop a "supplier rating"? Would the introduction of vendor rating data improve creditworthiness models?"

This research question represents the last step of our research and its ultimate objective is to formulate a new credit scoring model that can combine the information coming from vendor rating systems with the financial ones in order to improve the way credit risk is evaluated. Our work aims to provide a constructive contribution to the literature review in this field, in fact, there is no evidence of previous researches that have tried to build a credit rating model with vendor rating variables. In this part, we will try to fill up the lack of an integrated approach in the credit scoring worthiness assessment.

7.1 The focus Group

In order to respond to the goals of the third research question, we have decided to use a focus group methodology. The reasons beyond this choice have been widely specified in chapter 4. The main objective of the focus group was to identify new procedures to improve short-term funding inside of supply chains thought a greater exchange of information and informative transparency between firms and financial institutions. In other words, the participants understood the need of developing a new credit rating model that combines financial parameters with other kind of information coming from the supply chain redefining the default risk associated to each supplier. The focus group has been conducted without direct question, but letting the participants discuss about the topic of "Creditworthiness and Vendor Rating" so that their perception wouldn't have been influenced. Proponents of 19 companies have been involved in three different meetings. Companies involved were banks, companies belonging to a supply chain and service providers. The table of participants is revived below:

Industry	Partecipant	Role
Industrial Companies	Ariston	Procurement Director
	Boldrocchi	Investment Manager
	Bticino	Chief Procurement Officer
	Caruso	Chief Procurement Officer
	Frinsa	CFO
	Industrie Saleri Italo	Supply Chain Manager
	Sanofi Aventis	Chief Procurement Officer
	Thomson Reuters	Governance Risk and Compliance
Financial institution	Banca Sella	Innovation manager
	BPER Banca	Marketing
	Groupama	Financial Analyst
Information Provider	ACMI	Business Development Manager
	ADACI	Vice-President Regione Lombardia
	Assolombarda	Financial Credit director
	Cerved	Marketing
	CRIBIS	Marketing
	FS2A	Owner
	Niuma	Technical Manager
	AvantGarde Group	Analyst

Table 7.1 Detail of members of Focus group

Table 7.1 highlights how a very heterogeneous group has been set up. Participants were very different both in terms of industry's provenance and of role inside the companies. These meetings have produced a lot of insights on the theme. Some of them are not strictly related to our research, but some understandings have been fundamental to better understand how different economical actors perceive the topic of Supply Chain Finance. As already specified, three meetings have been organized and in the following pages the main achievements of each meeting will be listed.

7.1.1 First meeting: Environment analysis and problem recognition

In the first meeting, the focus was on understanding the environment where supply chain finance operates and recognizing the need of taking into account vendor rating variable when evaluating the credit risk of a company. Thanks to the analysis made in RQ1, we demonstrated that the information coming from vendor rating systems and the traditional ratings are not consistent. In particular, four different scenarios wer identified when assessing the credit risk of a company. These scenarios have been discussed in the focus group and are represented in the following chart.

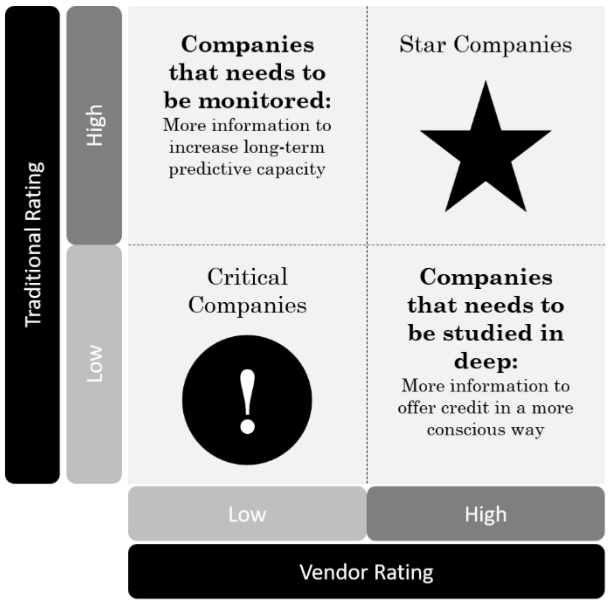

Figure 7.1 Matrix Vendor Rating vs Traditional Rating

The focus group identified two easily explicable situations: the ones for which the two dimensions are concordant. We won't waste more words on those scenarios, instead it is interesting to focus on the issues that came out from the analysis other two situations. In one case companies have a high performance in the traditional ratings model, but poor ones in terms of vendor rating. It is important to monitor this kind of companies, because vendor rating performances give information about the real-time trend. Thus, if they are poor, in the future even financial performances will decrease. This kind of companies are perceived as “safe” by the financial institutions, but, as we have just shown, a deeper investigation about the vendor rating dimension should be done in order to have a clearer view of the creditworthiness of these companies. In the other case, we find the opposite situation. As before, the focus group highlighted that there is the need to study in deep this kind of companies. In fact, despite of their poor financial situation, their vendor rating performances are more than satisfactory. Their credit risk is usually considered as “risky”, but, in some cases, they may be safer than the companies previously analyzed. The focus group also identified some key words that can be associated to companies of each of the identified scenarios.

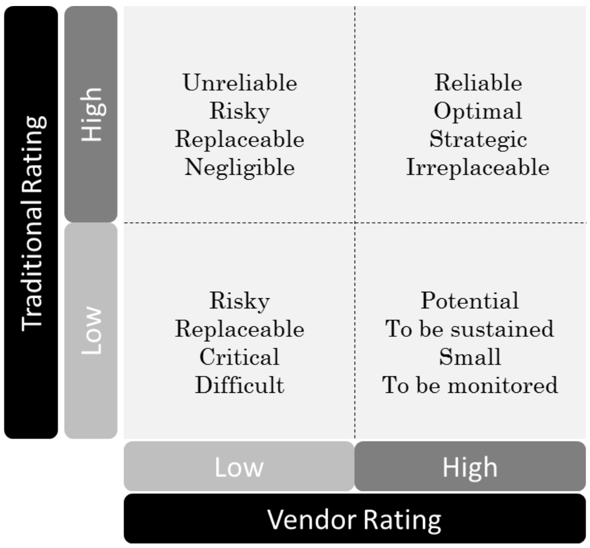

Figure 7.2 Description of each identified scenario

After this first discussion, two key issues have arisen. On one hand, the proponents of the banking sector have agreed about the fact that the financial rating is not enough to describe the real performances of a company. On the other hand, the focus group agreed about the need to create a new credit rating framework that can collect the data coming from either the vendor rating systems and the balance sheets.

7.1.2 Second meeting: Problem setting and requirements analysis

Before the second meeting, the focus group was asked to think about how the integrated framework should be built and what problem could arise in its creation. In the meeting, the focus group recognized the necessity of an intuitive, aggregate and qualitative rating. The final credit rating given to a company should be unique, but financial institutions should also provide the ratings that the company has in each of the dimensions that are considered. Firstly, the focus group decided to focus on how vendor rating information should be assembled in order to create a, so called, *Supplier Rating*. Before the designing of a formula, some issues have arisen:

- The strategic importance of the supplier for the customer should be categorized in: strategic, important, minor, in test phase.
- The weight of the supply on the total revenues of the supplier should be evaluated: > 50%, 25 – 50%, 10 – 25% and <10%.
- The duration of the relationship between customers and suppliers should be classified in: < 6 months, 6months – 2 years, 2 – 5 years and > 5 years.
- The attention, then, has been pointed out also on the periodicity of the vendor rating evaluation. Recent evaluations must be associated with greater weights (as in the financial ratings with frequent updating). Evaluation should be provided weekly, monthly, quarterly or biannually. On the contrary, annual evaluations should be avoided since they won't give a dynamic picture of the company.

Thus, the focus group recognized that the supplier rating should gain importance only when the relationship between the customer and the supplier is deep. Otherwise, the information given by vendor rating data are not useful. After the second meeting, the focus group had a better view on the problem and it was ready to design a solution.

7.1.3 Third meeting: Design of the solution

In this last meeting, the main goal was to develop an algorithm that can be used to evaluate the Supplier Rating of a company. The focus group ended up with this formula:

$$Supplier\ Rating = \frac{\sum_{i=1}^{n}(Customer\ Evaluation_i \times\ Customer\ Weight_i)}{\sum_{i=1}^{n} Customer\ Weight_i}$$

This formula highlights the importance that the customer weight must have in the definition of the supplier rating. This part has been introduced because, in the final evaluation of a supplier, a greater weight is associated at the judgments provided by customers for which the supplier is strategic and their relationship is long lasting. In particular, the customer weight is calculated in the following way:

$$Customer\ Weight_i = \frac{(Strategic\ Weight_i + Relationship\ Duration\ Weight_i)}{2}$$

The focus group also specified as those weights have to be selected:

Strategic importance	0.25 → Pre-Test
	0.5 → Minor
	0.75 → Important
	1 → Strategic
Relationship Duration	0.25 → until 6 months
	0.5 → from 6 months to 2 years
	0.75 → from 2 to 5 years
	1 → more than 5 years

Table 7.2 Description of the elements of the Customer Weight

The second part of the Supplier Rating formula is the Customer Evaluation. The focus group, also, identified the dimensions of vendor rating that have to be taken into account when assessing the rating. They are listed in the following chart:

Quality of the product	It refers to the value perceived from the client and its level of satisfaction.
Punctuality	It indicates the ability of the supplier in meeting deadlines respect to customer's requests.
Pricing Factors	It is related on how the pricing is in line with the services offered by the supplier.
Flexibility	It refers to the ability of adaptation that the supplier has in meeting customer's request
Relationship and skills management	It is about the quality of the relationship supplier/customer and the level of competencies of the supplier's workers.

Table 7.3 Description of Supplier Rating dimensions

A judgement needs to be given by the customer for each those dimensions of the supplier: 1 if insufficient, 2 if acceptable, 3 if good and 4 if excellent. The focus group recognized that there is no need to put a further weight on each dimension because they all have the same level of importance. Assigning a weight would be misleading for two different reasons: on one hand, different industries may perceive different importance to each dimension and, on the other hand, evaluation could come up from assigning weights to a dimension which is not objective, since it is influenced by personal considerations. In the end, these dimensions are connected in the following formula.

$$Customer\ Evaluation_i = \frac{(Quality_i + Punctuality_i + Pricing\ Factors_i + Flexibility_i + Relationship_i)}{5}$$

7.2 "Supplier Advisor"

So far, the "supplier rating" has been introduced as a theoretical concept defining *what* should be integrated in the framework but the discussion in focus group went further. In fact, the participants discussed also about *how* integrate it practically.

In the current scenario, vendor rating data are mainly stored only in buyers' informative systems to support their own decision making. In some cases, vendor performances are shared with suppliers but only for the purpose of driving performance improvement within the boundaries of the buyer-supplier relationship. However, there is no evidence of vendor rating data that are disclosed to other stakeholder within the supply-chain (banks and financial institution). Two options were discussed about the disclosure mode: sharing real existing vendor rating data or creating a new platform based on the "trip advisor" model, applied to B2B relationships. The focus group agreed for the second option.

This solution consists in the creation of a platform in which each company must register and accept the conditions.

The platform should be managed by an external actor, an information provider, that act as a middle-agent that centralize all the vendor rating data, elaborate them and make them accessible for other stakeholders.

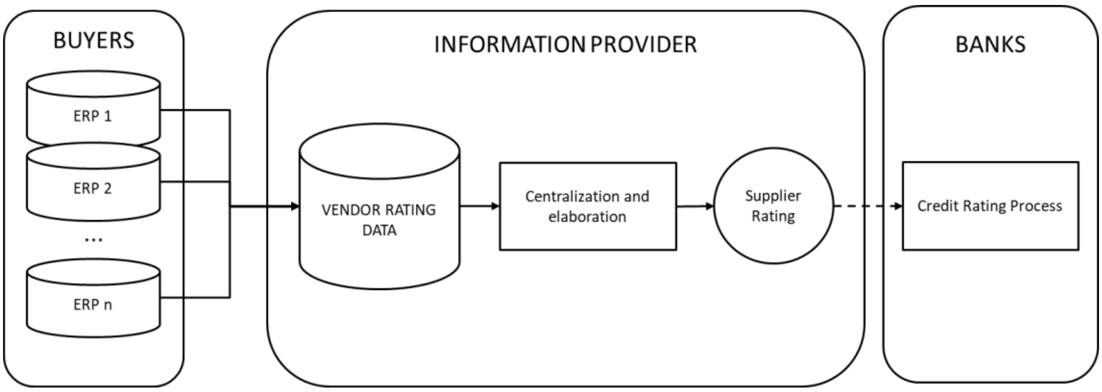

Figure 7.3 The architecture of "supplier platform" integration with credit rating process

For each supplier, a several information will be available. There are at least two possible use case of this platform:

- *Scouting*: buyers that need to find best suppliers could integrate their own scouting process with the evaluations that other buyers (and competitors) have assigned to potential suppliers.

- *Creditworthiness*: banks and financial institutions can access the database to obtain further information about a debt issuer. The integration between financial and operative performance will be completed.

Benefits

This innovative platform would allow the whole supply-chain to exploit the value of vendor rating data. Banks could benefit by improving the creditworthiness assessment process and, thus, reducing their exposure to risk due to lower credit deterioration. Suppliers can benefit thanks to an easier access to credit due to a more reliable assessment from banks. In particular, for all those suppliers that currently present an unclear situation between financial and operative rating, this second perspective can provide a good chance to get credit at a more sustainable cost of debt. Finally, buyers could benefits, indirectly, of the easier access to funds of their suppliers. In fact, if suppliers do not struggle to find funds, the whole supply chain can benefit from an increased stability and buyers can reduce the supply-chain risk. The three pillars of SCF on which the platform is build are the following:

- *Simplicity*: evaluation system will be simple, based on few significant information and flexible to adapt to different industries.
- *Transparency*: all the users of the platform will be identified and every dispute will be managed
- *Accessibility*: the database will be open and free to every user who want to access.

Challenges

This solution has also some challenges.

- *Regulation*: particular attention must be brought in the compliance with Basel requirements. In fact, banks must always refer to Basel as far as credit rating process is concerned. Since banks should make a change on how they currently assign ratings, a careful analysis of potential regulation obstacles should be performed.

- *Incentives to buyers*: since buyers are the real owners of vendor rating data, they must be incentivized in sharing them outside. In fact, such shared platform increased their value exponentially as the number of members increases. This is not a trivial point since vendor rating data represent an asset for buyers, thus, the option of disclose them must provide higher benefits to them. As already pointed out in *benefits* section, they could indirectly benefit from a increased stability of the overall supply-chain.

7.3 Results

The focus group was born with the aim of developing and introducing alternative methodologies of assessing companies' creditworthiness and it has been successful in this challenge. In fact, from focus group session, it has been identified a new weighting system and an algorithm for the evaluation of a company based on the information coming from vendor rating systems. Thanks to the addition of the vendor rating dimension, the assessment of the credit risk of a company can go beyond the usage of economic and financial indicators as done traditionally by banks and other financial institutions. Thus, this opens a new topic about the accessibility of vendor rating information by financial institutions. In this context, the focus group recognized that open platforms, where customers evaluate their suppliers, could become a valuable source of information. Furthermore, the concept of supply chain credit risk has been introduced in the credit rating theme. In fact, the focus group highlighted that it important to assess the creditworthiness of the whole supply chain because it also affects the credit risk of each company.

CHAPTER 8 – BEYOND TRADITIONAL CREDITWORTHINESS MODELS

So far, the discussion has gone through all the research questions and, from each of them, important contributions are emerged. From RQ0, the importance of financial information in the determination of credit rating has been demonstrated. Furthermore, the RQ0 confirmed that Altman's Z" Score represents the most suitable model for non-manufacturing industries and emerging markets.

Afterwards, RQ1 provided insights about the value of the potential integration of vendor rating data inside creditworthiness models. In fact, it demonstrated that vendor rating data are not explained in any way neither by credit scoring models, nor by credit rating ones. The important contribution is that vendor rating data represents a piece of information that is not already present in traditional models.

Finally, RQ2 has focused on the integration of vendor rating data inside creditworthiness model. The approach has been more practical than in the previous two RQs. From the three meetings of the focus group, two key-insights have been produced. First, expert members from many industries have confirmed the importance of including vendor rating perspective in the evaluation process of creditworthiness. Second, the discussion dealt with more practical issues as one of the major outputs of the focus group is a detailed concept of how the supplier rating could be practically implemented. Finally, the discussion addressed also technical specifications of this informative platform.

Our work demonstrated that a credit scoring model is an appropriate tool to determine a company's credit risk and that financial indicators and information coming from vendor rating systems are not consistent between them. In addition, the focus group supplied us with insights on how to deal with vendor rating data providing a reliable algorithm to assess companies' creditworthiness in operating terms.

However, as already discussed this research has proven that the financial perspective needs to be integrated with other sources of information in order to have a greater knowledge about the company's probability of default. Having a more complete assessment of a company's risk-profile brings benefits both for the borrower, that is evaluated based on a more reliable process, and for the lender, that can minimize losses from insolvent counterparts and can maximize profits.

A final contribution of this research is the concept of supply chain oriented creditworthiness framework. In the following paragraphs, each component of this innovative model is introduced. All the following considerations are the results of the previous analysis performed in this research. A combination of literature analysis, statistical models and focus groups has led to the creation of the following conceptual framework.

In the following figure, a visual representation of our creditworthiness framework is reported. In conclusion of the chapter, a brief explanation for each section of the framework is provided.

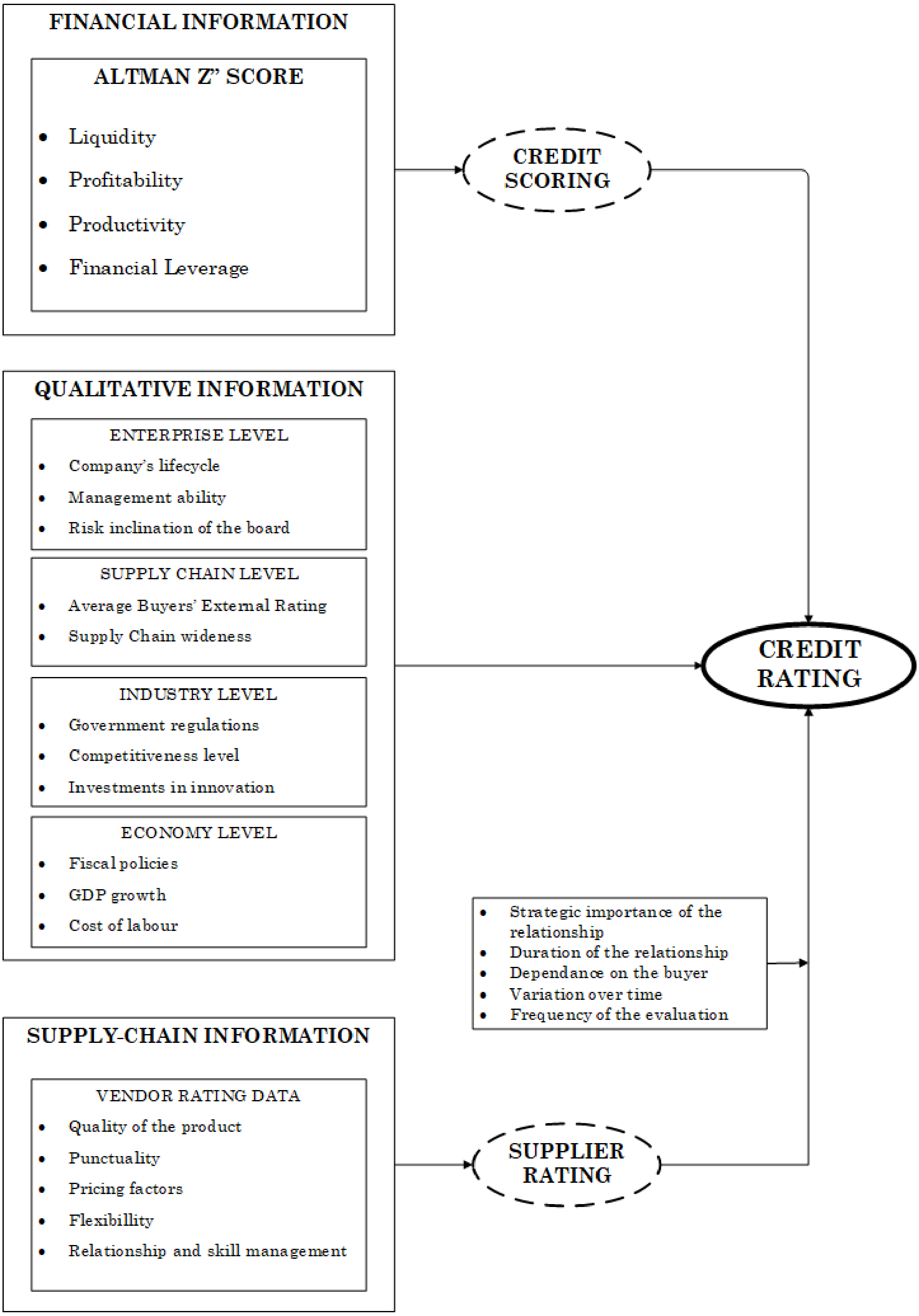

Table 8.1 The supply-chain oriented creditworthiness framework

8.1 Financial Information

First, the financial dimension remains the most important source of information of the framework since financial ratios look at many aspects of a business. For example, liquidity ratios measure the availability of cash to pay debt. Activity ratios measure how quickly a firm converts non-cash assets to cash assets. Debt ratios measure the firm's ability to repay long-term debt. Profitability ratios measure the firm's use of its assets and control of its expenses to generate an acceptable rate of return. Market ratios measure investor response to owning a company's stock and also the cost of issuing stock. Thus, financial ratios are fundamental to have a complete picture of the economic situation of a company.

In the framework, the Z"-Score of Altman has been selected as the reference for the financial dimension. This choice has been made because we demonstrated in the first research question that it is highly correlated with the BPER rating. The Z"-Score is particularly suitable to firms not traded publicly and to non-manufacturing entities, which are the companies that could have greater advantages from a new and more integrated credit scoring framework. In fact, big companies with consolidated financial structures easily have great performances in the financial dimension and, so, in the credit rating since it is deeply influenced by that dimension. The Z"-Score of Altman is made of four variables, each looking the company from a distinct perspective:

$$X_1 = \frac{Working\ capital}{Total\ assets}$$

It is a measure of the net liquid assets of the firm relative to total capitalization. A firm experiencing consistent operating losses will have shrinking current assets respect to total assets. Liquidity and size characteristics deeply influence this variable. X_1 is a liquidity ratio and, so, it measures e a company's ability to pay debt obligations.

$$X_2 = \frac{Retained\ earnings}{Total\ assets}$$

Retained earnings represents the total amount of reinvested earnings and/or losses of a firm over its entire life. This ratio measures the cumulative profitability of a company over time, so, the age of the firm is implicitly considered in it. For example, a new born company will have a low X_2 because it has not had time to build up its cumulative profits. It looks like that young companies may be discriminated by this analysis, but this is the situation of the real world. According to Dun & Brandstreet, approximately 50 percent of the firms that defaulted in 1993 had five or less years of lifetime. This ratio measures the leverage of a company. In other words, it looks at how much capital comes in the form of debt (loans) and of equity.

$$X_3 = \frac{Earnings\ before\ interests\ and\ taxes}{Total\ assets}$$

This ratio is a measure of the productivity of the firm's assets, independent of any tax of leverage factors. Profitability ratios are used to assess a business's ability to generate earnings compared to its expenses and other relevant costs incurred during a specific period of time. It is particularly important to take into account the profitability aspect since it is strictly connected with corporate defaults.

$$X_4 = \frac{Book\ value\ of\ equity}{Book\ value\ of\ total\ debt}$$

This measure shows how much the firm's assets can decline in value before the liabilities exceed the assets and the firm become insolvent. This ratio is used to evaluate a company's financial leverage which is the degree to which a company uses debt instruments respect to equity. The more debt financing a company uses, the higher its financial leverage. A high degree of financial leverage means high interest payments, which negatively affect the company's profits.

$$Z'' = 6.56\,X_1 + 3.26\,X_2 + 6.72\,X_3 + 1.05\,X_4$$

Thus, several company's dimensions have been taken into account thanks to this model that we consider the basis of our credit rating framework.

It is worthy to notice that financial information does not have any drivers that influence the impact that financial data has on the final credit rating. This is because the importance of financial information in the determination of credit rating has been widely demonstrated in literature and, thus, our framework does not try to change these priorities. In the following paragraph, the drivers for the weight of vendor rating data will be introduced.

8.2 Supply-Chain Information

Vendor rating data represent the innovative perspective introduced by this research. RQ1 demonstrated that the information coming from vendor rating systems and the financial ratios are inconsistent between each other. In RQ2, the focus group have developed a framework to determine whether a company has good operating performances or not. As already discussed, it is important to include this dimension in or analysis since financial information gives only a partial view of the creditworthiness of a company.

Another important upside of vendor rating information is that they are more responsive about variation in time. In fact, once a strategic or operational decision is made, the first effect is visible on operative performances. Instead, it can take years before the same effects is visible in financial statements. Furthermore, financial ratios look at the past of the company (a quarter, a semester, a year…) and can be misleading to predict the future. As financial factors are mostly backward-oriented measures, a credit rating model built only with financial ratios is inherently constrained. Thus, a more reactive source of information is needed and vendor rating data can be an answer.

Also, the predictive time-horizon would be affected by the integration of operative performances in the model. In fact, according to literature, the Altman's Z" Score predicts the probability of default in a two-years timeframe. On the other side, vendor rating data would represent a *weak early signal* that could dramatically reduce that predictive time horizon. Banks and financial institutions could exploit information coming from vendor rating analysis to receive anticipatory alerts about companies' status. Thus, an integrated view would increase the predictive power of the model.

As already introduced in Chapter 7, in the focus group methodology, the discussion between experts in this field provided the following formula for the calculation of the supplier rating:

$$Supplier\ Rating = \frac{\sum_{i=1}^{n}(Customer\ Evaluation_i * Customer\ Weight_i)}{\sum_{i=1}^{n} Customer\ Weight_i}$$

This calculation provide a synthetic value for the rating that buyers give to each supplier in the competitive arena. The value that this metric can have in the creditworthiness evaluation depends on some characteristics of the data.

As it is visible in the figure, the impact that supplier rating has on the final determination of credit rating is driven by some variables:

- **Strategic importance of the relationship**: the more strategic are the relationships that are rated, the more weight they have in the determination of credit rating. On the contrary, vendor rating scores coming from casual or spot relationships would not affect the assessment.
- **Duration of the relationship**: vendor rating evaluations produced in long-lasting relationships are more likely to provide significant insights about the company actual operative performance.
- **Dependence on the buyer**: the more a supplier is dependent on a single buyer (i.e. most of the revenue shares are given by a single buyer), the more creditworthiness analysis should be sensitive to possible fluctuations of those ratings.
- **Variation over time**: the more a supplier rating fluctuate in the same time horizon, the more its further analysis is worth it. In fact, a "flat" supplier rating trend would not provide many signals about potential alerts.

- **Frequency of the evaluation**: the more frequent and complete supplier rating are, the more reliability they have in the determination of credit rating.

8.3 Qualitative Information

The last piece of the puzzle is represented by the qualitative information that banks and financial institution evaluate when assessing creditworthiness of a borrower. After financial information and vendor rating information, more qualitative information needs to be included as well.

In traditional credit rating models, this category of information include general information that are not structured and cannot be processed as numerical data for analysis. Issuer rating does not depend only on the company itself, but also on the environment in which the issuer operates. These aggregated sources of information are a useful starting point for the analyst to understand the economic and financial environments in which a firm is operating.

Qualitative information can focus on three different levels: *enterprise, supply-chain* and *industry and economy*.

Enterprise level

There are several qualitative issues about a company's activity that cannot be summarized by an objective rating. For instance, the company's lifecycle is a significant information that can help interpret financial information from a different point of view. The financial statements of a small start-up company should be read differently from the ones of a giant mature market-leader firm.

Furthermore, management's ability is a key-competence that is impossible to summarize with an objective rating. Thus, a qualitative judgement about the efficacy of the management should be performed every time a firm is assessed. Together with the ability of management, the risk inclination of the board is a proxy of the impact of unexpected events that might affect the company.

Supply chain level

Some qualitative factors relate with the supply-chain where the company operates. Traditionally those factors are about the position of the company in the market: market share, competitiveness, diversification in terms of products and key customers and the ability to maintain or dictate prices in the market.

Two key-aspects about supply-chain configuration that can be useful in the evaluation of creditworthiness:

- *Average buyers' credit rating:* it represents the average credit rating that all the buyers of the focal company have. The rationale behind this is that the more risky are my buyers, the more risky I am. Taking into account the average cost of debt of buyers, a more accurate evaluation of the supplier's default probability is possible.
- *Supply chain wideness:* this "light" information deals with the export and import level of a supplier. It implies that the wider the buying network, the less risky is its revenues stream. In fact, it means that the business is differentiated enough to not depend on a single market. The same reasoning is applicable for import.

Industry level

After studying enterprise and supply-chain qualitative information, a focus on the industry is required. Developments in the industry, performance of companies, products coming to the market and government regulations can affect the performance of a company and, so, its creditworthiness. Industry factors can deeply influence the success or the failure of a company and, so, it is fundamental to determine the issuer rating in relation to the context of the industry in which the issuer is operating. As credit ratings are an evaluation of the issuer's ability to pay any debt back in the medium-long term, the rating needs to take into account the nature of the business cycle and specifically factors such as the cyclicality or volatility of the business. The general state of the industry or the level of competitiveness and capital intensity are other industry factors that condition the default risk of a company since they affect cash flow and the company's ability to meet obligations in time.

Economy level

An overview also to the overall macroeconomic situation is important to determine the credit rating of a borrower. A number of factors such as capacity utilization, monetary and fiscal policies, level of disposable personal income, inflation, interest rates, and GDP growth influence the economy and labor cost. Thus, these data are peculiar of a specific context or country but they are relevant because they can affect the evaluation of a borrower creditworthiness.

8.4 Conclusions

This chapter had the objective of introducing our personal contribution to future research. The output is a theoretical framework that can be considered a starting point for the practical development. The most important achievement is that three different categories of information have been put together with the final aim of improving the way companies' creditworthiness is assessed.

According to literature review and also to the focus group experience, banks and financial institutions should not look at a single synthetic rating to make decision weather a company is worthy to receive a loan or not. In fact, in the previous RQs, we have demonstrated that the financial perspective alone can bring to misleading results. Thus, financial institutions should investigate the rating that a company receives even in the operational dimension since it is useful to have a better picture of the whole situation. In this way, financial institutions would have two meaningful judgements to assess creditworthiness.

The idea is that, at first, the financial rating and the *supplier rating* should be analyzed separately. Afterwards, a final synthetic rating could be produced and assigned to the borrower. The idea of splitting the rating in different parts can be useful for both banks and companies. Banks could easily look at the performances that a company has both in the financial and operational dimension while companies could know in which dimensions they should invest in order to improve their final rating.

This integrated view can be useful for all the actors that have been considered in this research. Banks could have available a more effective tool that can depict the creditworthiness situation of a company from a new integrated view. Even if financial variables remain the most important dimension, the adjustments given by the supply chain perspective can results determinant in recognizing "good" and "bad" companies. In this way, on one side, banks can reduce the total risks faced that is one of their most important objectives, and, on the other, they can enlarge the credit supply to companies that were outside their vision increasing their profits.

Concerning companies, they will not feel any more the idea of being discriminated by their small dimension and they would perceive of being judged in a more trustworthy way. In addition, companies would not tie themselves to improve financial performances forgetting to invest in operational activities. Thus, the level of investments could increase from the moment that an improvement of the operational performances corresponds to an enhancing of the creditworthiness evaluation.

In the end, a more effective way to predict companies' default can bring advantages also to the whole supply chain. Big buyers could benefit by an increased stability of the upstream supply chain. Buyers can more easily control their suppliers and the risk of supply-chain disruption due to supplier's default would be minimized.

We are aware of the fact that our results are theoretical preliminary work, and further studies must be done in this direction. However, this has been a first successful attempt to merge the operational and the financial dimensions in the creditworthiness' topic. Even if we are far from the possibility of an implementation by financial institution, it is important to stress their attention towards these issues. We do not expect a revolution about the way credit rating is assessed. In fact, in a first introductory phase, *supplier rating* could play a supporting role. In fact, credit rating models represent the core-process of banks and implementing changes is not so straight-forward. At first, banks could use supplier rating with a "validation" function. This means that banks would continue using their financial credit rating as main source for their decision in the creditworthiness theme. However, a cross-examination must be carried out in order to identify possible inconsistencies between the credit rating and the supplier one. Eventually, an alert would suggest proceeding with further investigation about the nature of those discrepancies.

CHAPTER 9
CONCLUSIONS AND FUTURE DEVELOPMENT

9.1 Conclusions

The objective of this work was the development of an innovative supply-chain oriented creditworthiness framework. Given the early phase in which this field of study is, the approach of the present research was "theory-building", aiming at providing relevant contribution to existing research and future development. In this chapter, conclusions are summarized in order to formalize all the contributions that this work has given to the academic research.

The mentioned objective has been broken down into sub-objectives, named *research questions*. This process has been supported by a wide and systematic literature review.

Historically, banks and financial institution assess companies' creditworthiness mainly based on their financial statements. Thus, we can claim that there is a lack in research studies about a supply-chain oriented view to assess companies' creditworthiness. Furthermore, many researchers argue that the introduction of supply-chain information, would improve the effectiveness of credit rating models. There is extensive acknowledgment in literature that the effort to improve credit rating models should be redirected towards the pursuit of new information sources, rather than improving existing techniques.

This made us believe that it could be challenging and somehow helpful to investigate the impact of supply-chain variables on credit rating models.

The state-of-art of the literature, led us to the formulation of the following research questions:

- **RQ0:** this introductory question aims to clarify how the credit rating is determined and, in particular, how much influence financial information have on the final credit rating score;
- **RQ1:** the second question introduces vendor rating data in the framework as the real innovative input of the model. Here, the goal is to investigate whether somehow the informative potential of vendor rating data is already explained by other variables in the model or not.
- **RQ2:** the final research question provides a theoretical framework for the elaboration and integration of vendor rating data into creditworthiness assessment process. The output is the confirmation that an integrated view would be beneficial for all the parties involved.

For each *research question*, conclusions are reported:

RQ0: Understanding determinants of credit rating

The aim of this research question is to investigate the relationship between BPER Banca rating and main acknowledged credit scoring models found in literature (Altman Z-Score, Altman Z'-Score, Altman Z"-Score, Ohlson O-Score, Zmijewski score). In order to answer to this question, we have performed several statistical tests which answered several doubts.

Thanks to the application of Spearman's correlation test, we can state that there is consistency between all credit-scoring models and the BPER Banca rating. Among all the credit scoring models, Altman Z"-Score resulted the "best-fitting" model for our sample formed mostly by Italian SMEs. Furthermore, Altman Z"-Score has a strong correlation with credit rating. This means that financial variables, which are used in credit scoring models, are an important source of information also for more complex credit rating models that consider also qualitative aspects (i.e. enterprise strategy, macroeconomic environment…).

Afterwards, a One-Way ANOVA have been performed between the BPER Banca rating and Altman Z"-Score. It demonstrated that there is a statistically significant different of the BPER Banca rating among the Z"-Score clusters identified by Altman. In other words, companies that Altman's Z"-Score classifies as high-risk profile has an average BPER credit rating that is significantly higher than the other two groups. The behavior of the two dimensions is concordant.

Thanks to the statistical methodologies (Spearman's correlation coefficient and ANOVA analysis) the rationale behind a complex credit rating model such as the BPER one has been clarified. This has a useful foundation for the development of the supply chain oriented creditworthiness framework.

RQ1: Evaluation the potential of vendor rating data

The second research question focused on understanding whether the introduction of vendor rating data would bring additional information to the model or it is just a redundant dimension.

Analysis in this direction are needed to discover the variability of operative performance (measured by vendor rating data) is already "explained" by credit scoring or credit rating variation. Thus, statistical methodologies have been applied in order to have reliable results.

From the analysis of the results provided both by Student's t-tests and two-axis matrixes, it is possible to conclude that there is no correlation between vendor rating data and the other variables. Neither credit scoring, nor credit rating shows a significant compatibility with vendor rating data. On the contrary, the financial (Z"-Score and BPER) and the operational (Vendor rating) dimensions are not consistent in almost the 50% of the total cases. This is a first proof of the fact that there is the need of looking at both of the scorings to better depict the creditworthiness of a company.

This represents an unexplored topic in the creditworthiness state-of-art literature. It might be that a valuable piece of information about company's overall status could be missing and, thus, an integrated view would provide a gain in the effectiveness of credit rating models.

RQ2: Integrated supply chain oriented creditworthiness framework

This research question represents the last step of our research and its ultimate objective is the formulation a new credit scoring model that can combine information coming from vendor rating with the financial ones in order to improve the way creditworthiness is evaluated. Our work aimed to provide a constructive contribution to the literature review in this field, since there is no evidence of previous researches that have tried to build a credit rating model with vendor rating variables.

The last research question is the *theory-building* one. Here, a qualitative technique, the *focus group*, has been used thanks to its good fit with the requirements of the RQ. The methodology followed a multi-step focus group articulated into three meetings, each one with a specific objective. Participants to the meetings were experts and managers coming from enterprises, banks and public institution of many different industries.

As first outcome, the focus group has formulated a synthetic indicator, called "*supplier rating*", that represents a synthetic measure of company's operative performances.

$$Supplier\ Rating = \frac{\sum_{i=1}^{n}(Customer\ Evaluation_i * Customer\ Weight_i)}{\sum_{i=1}^{n} Customer\ Weight_i}$$

Furthermore, the discussion in the focus group provides several insights and conclusions.

Among them:

- The integration of the supply-chain perspective within traditional models would improve the assessment of creditworthiness. The rationale behind is that lending institutions would have a more complete picture of the borrower creditworthiness situation since financial information are sometimes too restrictive.

- Vendor rating data could represent a *weak signal* to predict a company's insolvency. The worsening of vendor rating performances could be visible quicker than the same effect on financial statements. This would help the lender whether to accept or decline the debt issuer's request.

- Main benefit from this integration for banks and financial institutions is the lower risk exposure that would come from a better estimation of the probability of default of debt issuer. In this way, a better planning of capital requirement is possible, ensuring financial stability.

- Suppliers would benefit from the adoption of this integration thanks to a better assessment of their actual situation. Many suppliers that currently do not have access to credit due to their "bad-looking" financial statements, could get access to credit thanks to their positive vendor rating evaluations.

- Buyers would benefit thanks to an improved visibility and stability throughout the whole supply-chain.

Finally, our thesis concludes with a theoretical formulation of a supply-chain oriented creditworthiness framework. It represents the legacy that we would like to leave to the academic world hoping that it could be useful for further development in this field of study. We have tried to design an innovative credit rating framework that could collect information coming from three different perspectives: the financial, the supply chain and the qualitative one.

As already discussed in the paragraph 8.4, a supply chain oriented credit rating framework can be useful either for banks and for companies. On one side, financial institutions will have available a more reliable and effective tool to better depict the creditworthiness situation of their customers. On the other one, companies will be able to improve their credit rating either investing in operational activities or enhancing financial performances. The merge between the financial and the operational dimensions can bring advantages also to the supply chain. Big buyers could more easily control their suppliers and the risk of facing problem due to the default of an actor of the supply chain would reduce.

It is important to point out that this dissertation aims to augment the still scant literature related to the world of supply chain finance credit rating models and to suggest further practical analysis on the topic. In the following paragraph, some ideas about future possible developments will be presented.

9.2 Future development

The final paragraph of this thesis has the objective to introduce the reader to some "behind the scenes" reasoning that could help future development of academic literature.

As widely discussed earlier in literature review, the great relevance of creditworthiness has gained the attention of the academics since the beginning of the last century. By then, uncountable empirical studies have been performed on the topic, trying to push the performance limit of creditworthiness model by using new statistical approaches. This research has provided the reader with a supply chain oriented credit rating framework which can be seen as a solid theoretical fundamental for future studies in this field. In our case, some limitations in the dataset have not allowed the process of transforming our theoretical results in a practical credit rating model.

This paragraph aims to show which is the path and the steps to follow to develop such model and provide some guidelines to drive future research to overcome limitations that prevent this methodology to be fully applied in this research.

9.2.1 Limitations of the dataset

In this chapter, the focus is about showing which limitations we encountered in the original project and how future researches could overcome them by planning the study design accordingly.

Lack of default outcomes

This is the first fundamental assumption that must be met when a new default predictive model is developed. The key is being able to discriminate between defaulted and active companies.

In particular, it is necessary that the sample can be unequivocally split into two clusters, according to insolvency status: companies that went bankruptcy on one side versus companies that did not went bankruptcy, in a certain year t. This parting is extremely important because, if the model aims to predict reality, it needs to be designed based on real outcomes. In this way, the performances of the model can be assessed on the comparison between predicted default status vs real default status.

Our recommendation for future studies is that researchers must accurately design the data collection process, which is the fundamental step to develop a good-performing credit scoring model.

Lack of historical vendor rating data

A further requirement that data must have to obtain a reliable predictive model is complete historical records for each of the variables taken into account.

In particular, this is a complicated process when considering vendor rating variables. Differently from financial data, the collection and disclosure of vendor rating data is not mandatory. Thus, it is not uncommon to have partial historical records of vendor rating data.

In fact, a predictive model is evaluated on two-key aspects: accuracy and predictive time horizon power. The former is about how good the model is in discriminating between good and bad companies, while the latter represents how timely the model is in predicting default of a company.

In fact, ceteris paribus, a model that is able to predict earlier the default of a company is considered a better model.

To do so, the accuracy of predictive model must be analyzed backwards in time. The more a model is able to predict default throughout the years moving from the present to the past, the more the model is reliable.

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