TECHNICAL UNIVERSITY OF CRETE

MASTER IN TECHNOLOGY & INNOVATION MANAGEMENT

A new model of Venture Debt Rating

Master thesis by

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Abstract

Startups and early stage firms don't fulfill traditional lending criteria, which affects their access to credit. To mitigate this problem, the present thesis defines a credit rating framework (CRF) for early stage firms and proposes a basic CRF model. The CRF utilizes indicators in respect to venture lending criteria, credit risk modeling, VCs' quality and firms' performance, concluding to the basic model. The proposed CRF model includes and consolidates 6 models provided by the literature, related with firm's failure risk. Moreover, it allows the inclusion of additional models without losing its generality and consistency. Specifically, the basic CRF normalizes each model estimator on a relative scale of 5, benchmarked against firms with established credit ratings and provides an overall rating presented on a radar graph. The model leverages the rating scales of known rating agencies for the credit risk assessment of early stage firms. Generally, the proposed CRF tries to reduce the information asymmetry between lenders and early stage firms, aiming to improve the access of the latter to debt financing.

Keywords: Venture, Debt, Rating, Loan, Finance, Startups, Entrepreneurship.

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Introduction

Improving the access of startups and early stage firms to debt financing could be valuable for their growth and success. Such firms don't fulfill the traditional lending criteria (collateral, cash flows, track record, etc.) making the evaluation of their creditworthiness a challenging process.

The present thesis aims to reduce the information opacity in respect to early stage firms' credit risk, by proposing a Credit Rating Framework (CRF) for the connection of such firms with potential lenders. The proposed CRF is defined based on indicators for firms' performance, credit risk models, venture lending criteria and VCs' quality, which leads to a basic CRF model. The basic CRF model includes 6 models provided by the literature that are related with firm's failure risk. Particularly, the basic CRF normalizes each model estimator on a relative scale of 5, benchmarked against mature firms with established credit ratings, providing an overall rating represented on a radar graph. In the basic CRF, additional models could be consolidated while the model keeps its consistency and generality. The value of the CRF lies on the utilization of rating scales used by well-known rating agencies, for the evaluation of early stage firms' creditworthiness. The proposed CRF could be a useful tool for both lenders and firms and could be leveraged for credit risk modeling concepts.

Chapter 1- Setting the Credit Rating Framework (CRF)

1.1. Venture debt- An analysis of the debt instrument for startups

Venture debt (VD) is a form of debt for VC-backed companies that characterized by lack of collateral, negative cash flows and as such don't fulfill the traditional criteria to access debt.

Startups use venture loan to *support growth* with low cost of capital, to *reduce dilution* or to *extend cash runaway* in order to reach certain *milestones* or to achieve a *higher valuation* in subsequent equity round (Gordan, n.d.) (Fig.1).

VD is typically referring to the *senior term loan* (first priority in liquidation) with 3 to 5 year *maturity*. Moreover it requires a *blanket lien* on startup's assets and *warrants* for company stock. VD has a *flexible* structure and generally is a complement to prior equity financing, leveraging its due-diligence to reduce transaction cost (Gordan, n.d.).

Startups should *optimally* raise VD immediately after a VC round when cash is sufficient, due-diligence information is fresh and investors are optimistic. However, drawing the debt soon after the equity leads firms to pay down the debt long before they actually use the cash. Depending on VCs quality, firms could achieve a *delay* in the *draw-down period* or a 6-12 month *interest-only period* (Feinstein, Netterfield and Miller, n.d.).

VD *lenders* are generally *tech banks* and *non-bank* lenders (funds or finance companies). Because of bank regulatory requirements for lending (e.g. basel III, IV) *banks* usually offer *smaller loan amounts* compared to *non-banks* and loan terms may include covenants. However, *banks* offer *lower interest rates* while their incentive to lend derives from the fact that the startup may have to move its *banking relationship* to them (e.g. checking & savings accounts, letters of credit, cash management accounts, wire transfers). *Non-bank lenders* require *high interest rates* and *more warrants* (typically 10% of loan), to compensate for the high-risk that are taking, but also offer *larger loan amounts* and more *flexible* terms. In some cases non-bank lenders provide VD to startups that are not VC-backed (Findventuredebt.com, n.d.).

As it was denoted, venture lenders require a lien on the startup's assets that either includes *intellectual property* (IP) or excludes it with a *negative pledge*. The negative pledge states that startups agree not to pledge its IP to anyone else (Weyer, n.d.). Additionally, venture loan could include various *fees*, an aggregate table of VD terms is presented bellow (Table 1).

	Venture Debt	Convertible Debt	Working Capital Line
Description	A *non*-convertible, senior term loan that can be used like equity, and includes warrants	A loan that converts to stock in the next equity round, usually at a discount or with warrants	A revolving line of credit that is secured by working capital; may or may not include warrants
Repayment	Generally repaid in monthly payments over the life of the loan	None, converts to equity	Can flex up or down over the life of the loan, depending on the "borrowing base" securing the loan
Approximate Interest Rate	10-15%	3-8%	6-10%
Dilution	Generally a small fraction of equity (< 1%), due to warrants	Similar to equity, but can be more or less dilutive depending on valuation in the next round and specific terms	Minimal to none; may or may not include warrants
Default Clauses	Varies, but often limited to failure to repay	Generally none	Often includes MAC catch-all (any "material adverse change"), investor abandonment, etc.
Financial Covenants	Generally none	Generally none	Often bound to a minimum amount of cash, A/R, performance vs. plan, etc.

Fig.1: Different types of debt for startups (Gordan, n.d.)

Table 1. Venture Debt Terms (Columbia Lake Partners | Financing European Growth, n.d.)

Maturity Date	Typically, 3 years after closing date
Repayment	Typically 36 equal monthly payments, although there could be draw down periods
Availability	Draw down period & Multiple tranches
Interest Rates	Are paid monthly. Usually VD have fixed rate: 10-15%. Could also have floating rate (e.g. LIBOR+10%)
Security & Subordination	Senior Security & blanket lien on startups assets.
Warrants	For non-banks lenders is typically 10% of the loan amount
Origination Fee	A fee due upon funding of the loan
Prepayment Fee	A penalty for repaying the loan early
Maturity/End of-term Fee	A fee due at the loan maturity

Following some *data* about VD market are presented (Fig.2-7). Returns on venture loans are high, since, as it is further indicated, lenders compensate for the high prepayment risk (Gonzalez-Uribe and Mann, 2017).

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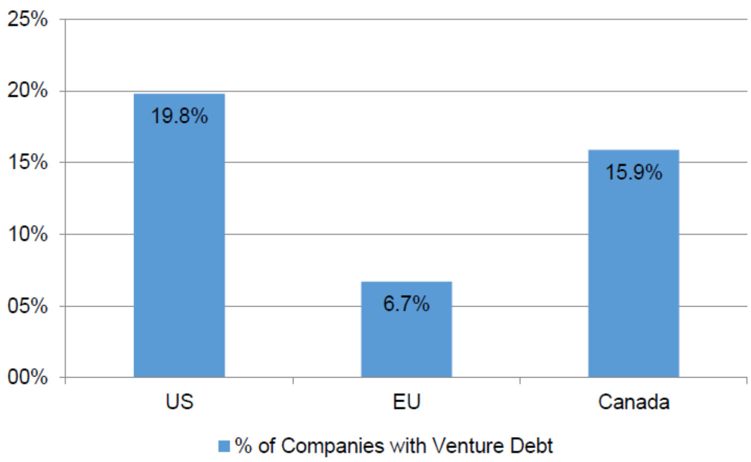

Fig.2: Fraction of VC-backed firms that raise VD based on Preqin dataset, for the period 2010-2015 (Durufll, Hellmann and Wilson, 2016)

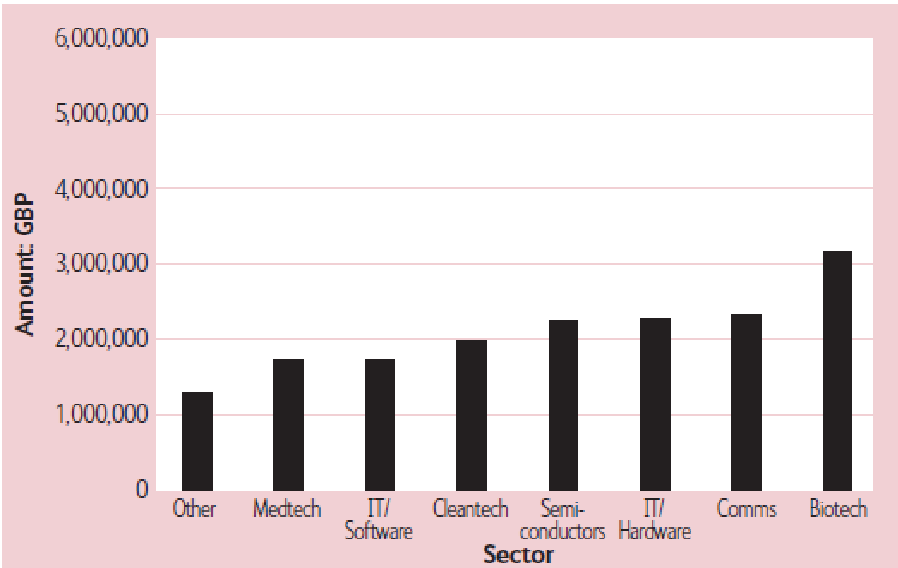

Fig.3: Sizes of VD investments by Sector. Data provided by BVCA (The Rise of Venture Debt in Europe, 2012).

Regarding the venture loan amount for early stages (Series A-B, pre-revenue), it was indicated that lenders typically commit 25%-50% of debt relative to the last equity round. For example, for a startup that raised a $4,000,000 in Series A, the debt raised soon after equals to $1,000,000-$2,000,000 (Weyer, n.d.).

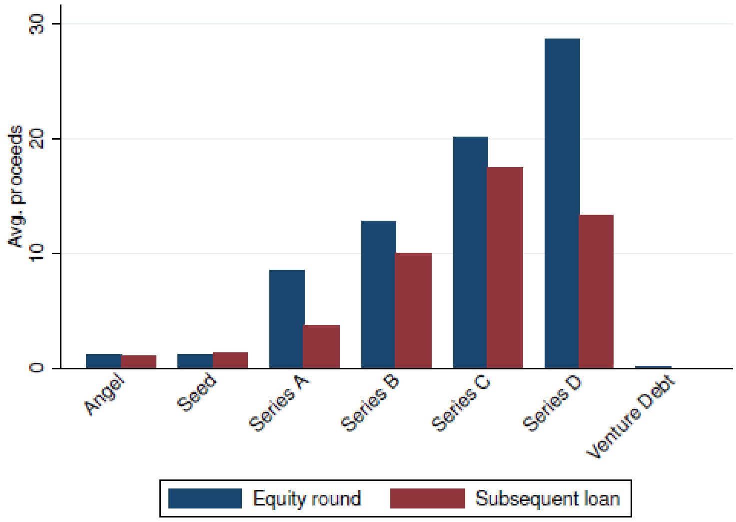

Fig.4: Venture loan & equity amounts by stage. Based on preqin dataset, for 2000-2013 (Gonzalez-Uribe and Mann, 2017)

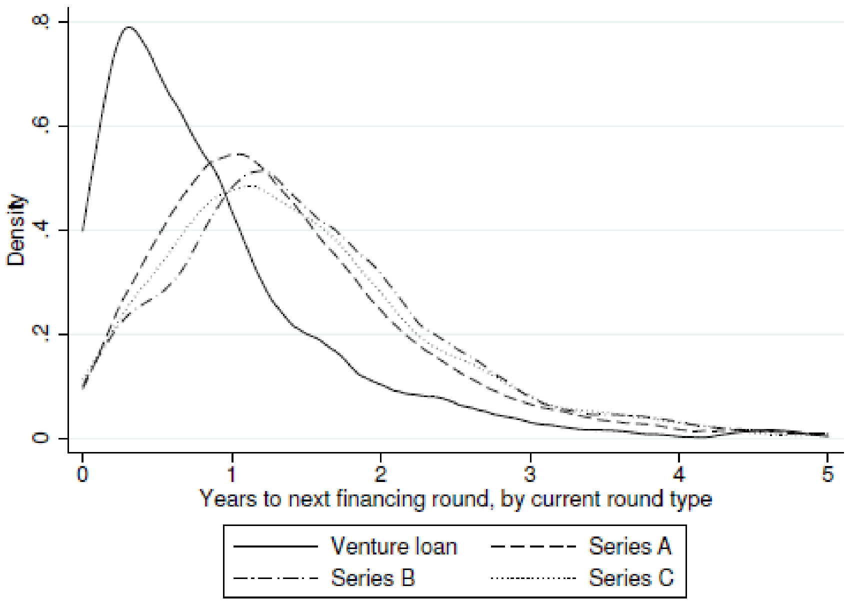

Fig.5: Years to subsequent financing round in respect to different round types. Based on preqin dataset, for 2000-2013 (Gonzalez-Uribe and Mann, 2017)

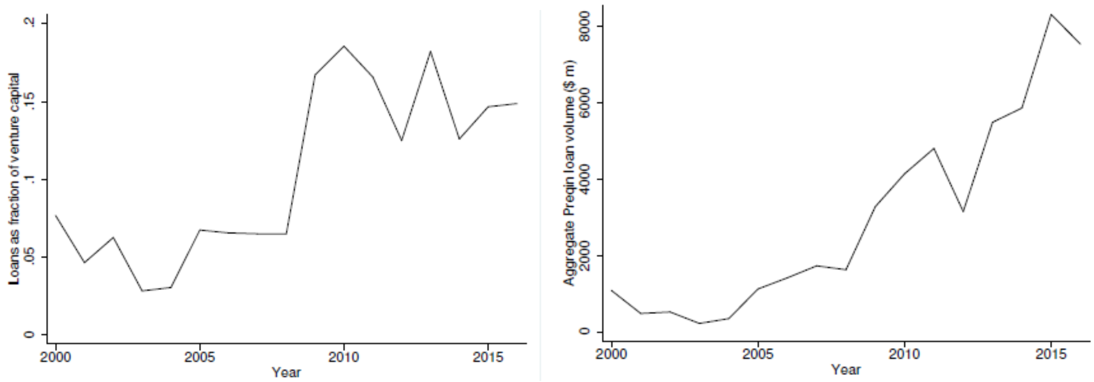

Fig.6: Venture loans as fraction of VC-financing (left) & aggregate volume of venture lending (right). Based on preqin dataset (Gonzalez-Uribe and Mann, 2017)

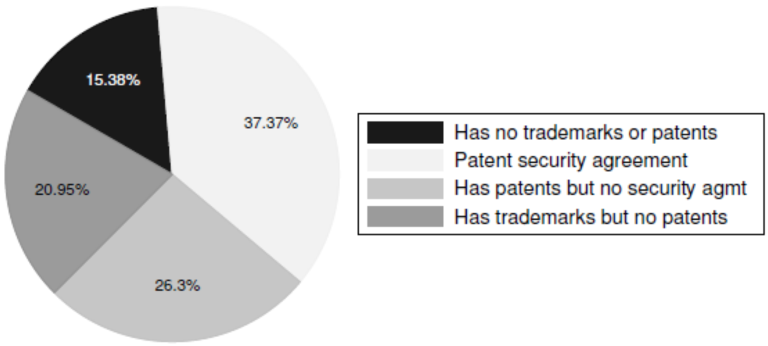

Fig.7: IP rights of startups that accessed VD. Based on preqin & USPTO datasets (Gonzalez-Uribe and Mann, 2017)

1.2. A proposal for a Credit rating framework (CRF) for early stage firms

A way to improve access of startups and early stage firms to debt financing is the creation of a credit rating framework for such firms. Although the proposed framework will differ from the traditional assessment criteria of mature firms, existing debt rating methodologies are used as a guide.

As it is described in Fig.8 and Fig.9 for mature firms, agencies *distinguish* among *Issuer credit rating* and *Issue credit rating*. Issuer rating refers to the firms' overall creditworthiness assessment and it indicates the probability to default in respect to all financial obligations. On the other hand, issue rating is firm's creditworthiness assessment with respect to a specific debt (issue) and it evaluates the potential for *recovery* in case of default. Specifically, it is indicated that non-investment grade ratings give additional weight to recovery (S&P Corporate Ratings Methodology, 2014).

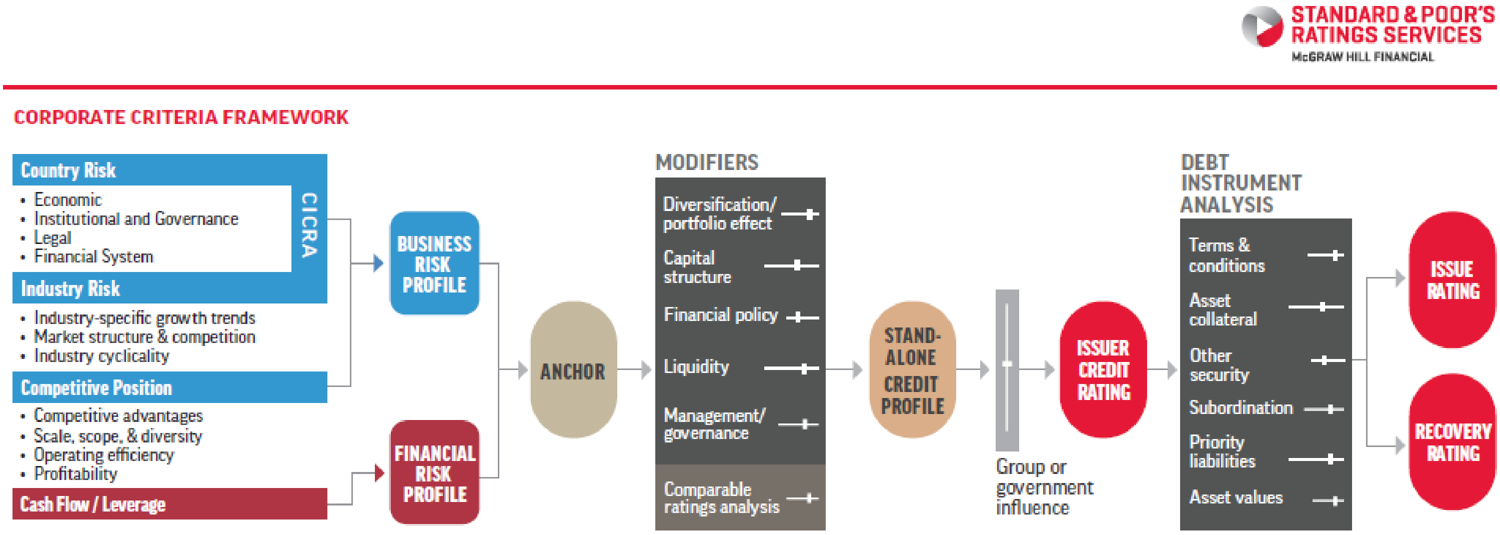

Fig.8: S&P credit rating methodology for mature companies (S&P Corporate Ratings Methodology, 2014)

RECOVERY RATINGS, RANGES & ISSUE RATINGS FOR SPECULATIVE-GRADE ISSUERS

Recovery Rating	Description of Recovery	Recovery Range[1]	Issue Rating Notches[3]
1+	Highest expectation, full recovery	100%[2]	+3
1	Very high recovery	90 - 100%	+2
2	Substantial recovery	70 - 90%	+1
3	Meaningful recovery	50 - 70%	0
4	Average recovery	30 - 50%	0
5	Modest recovery	10 - 30%	-1
6	Negligible recovery	0 - 10%	-2

[1]Recovery of principal plus accrued but unpaid interest at the time of default. [2]Very high confidence of full recovery resulting from significant overcollateralization or strong structural features. [3]Indicates issue rating "notches" relative to our issuer credit rating.

Fig.9: Issue Rating & Notching (S&P Corporate Ratings Methodology, 2014)

Similarly, in the CRF of, the concept of *notching* could be utilized. In this way the CRF should focus on the firm's ability to recover the loan and how this ability impacts its overall creditworthiness. Generally VD is structured in way that is compatible with the characteristics of high-tech startups, while startups' failure rate is substantially high.

1.3. CRF & loan structure

In regards to issue rating the *VD structure* should be assessed. Venture loans' *default rates* are quite *low*, while *prepayment risk* is *high*. Specifically, based on investment data of a specific venture Lender the estimated loss rate was about 3% (for 2016), which was close to the percentage of US high-yield default rates (Fig.10), however venture loans may have lower recovery rates (Gonzalez-Uribe and Mann, 2017).

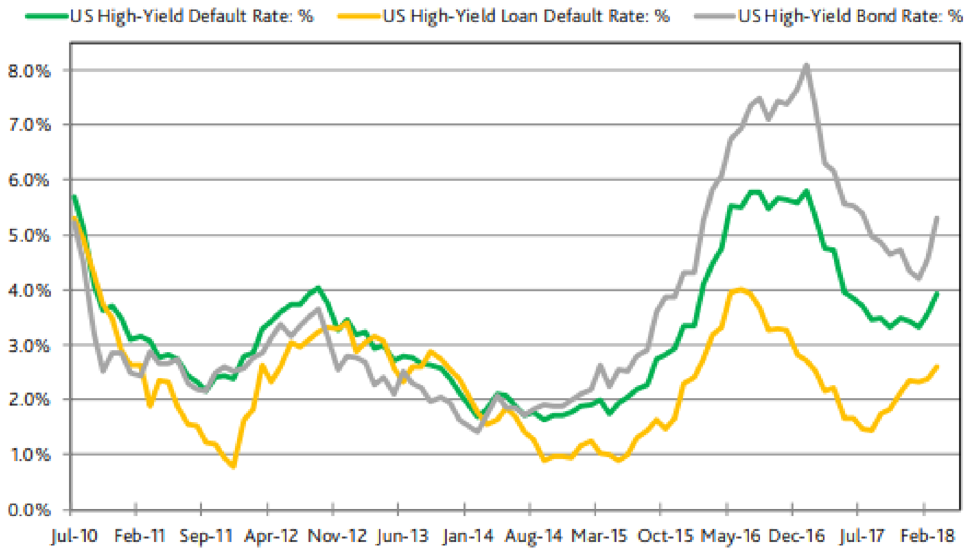

Fig.10: US high-yield default rates (Moody's Analytics Research, 2018)

In respect to debt recovery assessment the CRF considers the way lenders face the high prepayment risk. Usually, loan terms include prepayment and origination fees, those fees however are quite small. Another solution applied by venture lenders is *the end-of-term payments* that provide a guaranteed return, independently of the realized loan maturity (Gonzalez-Uribe and Mann, 2017).

Moreover, CRF should evaluate startup's ability to pledge its *intangible* assets as *collaterals*. VD is generally referring to *senior-term* loan, enhancing the firm's recovery rating. Additionally, it should be examined if the lien includes the IP or excludes it (*negative pledge*).

1.4. VD usage & CRF

The CRF should consider the bellow factors:

- Raising VD leads early stage firms to higher failure rates. Specifically, \$125,000 more venture debt predicts 6% higher closures. Nonetheless, conditional firm's survival, raising VD leads firms to 7-10% higher acquisition rates (Davis, Morse and Wang, 2018).
- Venture loan payments should account for *lower* than 25% of total *operating expenses*.

1.5. Modeling of Credit risk for startups & innovative SMEs

The proposed CRF could be based on the available credit risk models. Due to the regulatory frameworks for banks (e.g. basel IV,III) credit models have been highly valuable.

In respect to *startups* the usage of qualitative (soft) factors in credit risk models is highly significant. Gonçalves, Martins and Brandão (2014) studied the impact of *financial capital*, *human capital* and *industry dynamics* on startups' probability of default (PD) (Table 2). Default, is commonly defined as case where "credit obligation is overdue for more than 90 days". In addition, the study focused on the occurrence of the first credit event for the first three years of startups' life. Regarding, the *financial ratios*, five categories have been examined: *leverage*, *liquidity*, *profitability*, *coverage* and *activity/efficiency*. Referring to *industrial dynamics* the variables were: industry *growth*, *industry entry rate/barriers to entry*, *market concentration* and *economies of scale*. While the *human capital* factors analyzed were: *founders' education, founders' industry experience, founders' management experience* and *firm's business plan*. In Table 2 the statistically significant variables in respect to their impact on PD are presented.

Gonçalves, Martins and Brandão supported, that there isn't any statistically significant correlation of *industry dynamics variables and PD,* when the specific variables are aggregated with the financial and human capital ones. These findings may arise from the focus of this study in the first three years of the startups' life.

Similarly, in the early stage of a startup, is reported a poor performance with respect to profitability ratios, which is the reason that current study didn't support a statistically significant relationship of *profitability ratios – PD.* Moreover, they suggest that *short net debt recovery periods* will mitigate the default risk as they described it.

Table 2. Impact of financial and human capital variables on startups' default probability, within three years after their foundation (Gonçalves, Martins and Brandão, 2014)

Variable's Category	***Variable***	***Impact on* PD**
Leverage Ratio	**Solvability Ratio** Equity / Total Liabilities	Increase in ratio leads to a decrease in PD
	Financial Autonomy Ratio Equity / Total Assets	Increase in ratio leads to a decrease in PD
Coverage Ratio	**Debt to EBITDA Ratio** Net Debt/ EBITDA	Increase in ratio leads to an increase in PD
Activity/efficiency Ratio	**Asset Turnover Ratio** Net Sales / Total Assets	Increase in ratio leads to a decrease in PD
Human Capital	**Founders' Education**	High levels of Education leads to a decrease in PD
	Founders' Management Experience	High levels of management experience leads to a decrease in PD

In general, the estimation of the future profitability performance of startups is a very complex subject and significant for the assessment of their creditworthiness.

A main problem in the credibility assessment of Startups is the non–sufficient financial data they provide. Sohn and Kim (2012) develop a behavioral credit model for *new technology-based firms* (NTBFs), including startups and innovative SMEs (Table 3). Based on previous credit scoring models, the model focused on the financial reporting of firms after they received their loan and introduced the factor of *time* for assessing the different *states* of the financial ratios. Specifically, instead of using the firms' financial ratios (Table 4) the model used time series of nominal variables that represent different states of the ratios. The states were: "*no changes in financial ratio compared to previous year",* "*decrease in financial ratio compared to previous year*", "*increase in financial ratio compared to previous year*" and "*data for the financial ratio are not provided"*.

Table 3. Technology attributes & Economic factors associated with default rates (Sohn and Kim, 2012)

Technology attributes	Economic factors
Manager's knowledge and experience *Human resource & environment for R&D* *Management ability & fund supply* *Timely progress of business* *Market potential* *New technology development*	***Domestic Economic Factor:*** *Economic situations index of SMEs* *Economic preceding index* *Consumer price index(CPI)* *Earning rate of the national bonds in three years* ***Business Factor:*** *Business survey index* *Stock Price Index* *Total business environment index* ***Operation Factor:*** *Stock Price Index* *Operation index of SMEs*

Table 4. Financial ratios monitored after debt financing (Sohn and Kim, 2012)

Type of financial ratio	Financial Ratio
Growth	Growth rate of stockholder's equity
Profitability	ROA
Profitability	net profit/sales
Activity	Turnover of net worth

As they suggest, *high market potential* leads to *higher default rates*, due to the strong competiveness among firms. In addition, firms with intensive *technology development* or *timely progress of business* also had higher probability of default, since these two factors are related with large capital infusions. For the first year after the loan is received, firms that presented *decreasing net profit to sales* (annual change) had lower default rates compared to firms that didn't present the specific financial data. In response to the second year, the firms with *decreasing growth rate of stockholders' equity*, had a *higher default probability* compared to firms presented different financial status (increasing ratio or data not provided), while those with *decreasing ROA* had *lower default rates* compare to those didn't provide the specific ratio. Additionally, firms with *decreasing turnover of net worth* had higher probability of default in compare to those that didn't provide the relevant financial information. The significance of this model lies on its capability to take into account the case of missing financial data and also on the utilization of financial ratios trends.

Based on the above finding's the VCs' ability to support their portfolio firms in the stages with *intensive technology* development is highly significant. Moreover, VC-backed firms' financial performance after the loan is received is an important factor.

For *innovation factor*, Pederzoli, Thoma and Torricelli (2012), developed a credit risk model for the innovative SMEs & startups. The model has a two-year estimation period while the data needed, collected from the previous two fiscal years. The quantitative and qualitative factors that were statistically significant in regards to their impact on firm's PD are presented on Table 5. Although the study referred to low tech industries, it provided a *framework to measure the effect of firm's innovation* on its *credit risk*. As it was indicated one main problem is the *measurement of the patent value*:

- Patent application usually takes 18 months, so credit risk assessment for firms that applied for a patent should consider the case that the patent will not be granted.
- A longer period is needed for a patent to obtain forward citations.
- The firm's industry characteristics. Patent citations and the number of International Patent Classification classes differ for every industry segment.

To overcome this problem Pederzoli, Thoma and Torricelli suggested a *patent value index* that could also be used for startups credibility assessment. The index factors are presented below:

- The number of patent's inventors, is a sign of firm's R&D intensity and an indicator of its value.
- The international protection of a patent indicates a higher expectation of its values, since it is related with high filling costs.
- The number of patent's citations, show the technology's market potential or utility.
- The number of International Patent Classifications codes of a patent indicates high technology value and patent's utility among different technological classes.

Regarding the impact of innovation on credit risk modeling, the most significance finding was the fact that in order to assess the effect of firm's innovation on its PD, a *joint consideration of innovation with capital structure* was implied (Table 5). In particular, they introduced the variable: *Equity Ratio* Patent productivity*. The Table 5 also includes variables (profitability, coverage) that are relevant to SMEs that generate profits, in order for a more complete approach to be presented.

The proposed rating framework could consider the factors applied by the multicriteria credit rating model of Angilella and Mazzù (2015).

Table 6. Soft & Hard factors related to innovative SMEs' credit risk (Angilella and Mazzù, 2015)

Soft & Hard factors	Description
Innovation factors	• Intangible Assets/Fixed Assets • R&D/Sales
Financial ratios	• Short-term debt/Equity • ROA • Cash/Total Asset
Development risk	• Scientific skills • Awards
Production risk	• Availability of testing and pilot units • Granted patents
Market risk	• Key competitors • Potential market
Technology risk	• Technological capability, measured by comparing the level of competitiveness to the technology available

Table 5. Variables impacting innovative SMEs' PD (Pederzoli, Thoma and Torricelli, 2012)

Variable's Category	***Variable***	***Variable–PD Relationship***
Leverage Ratio	Equity / Total Debt *(Equity Ratio)*	Negative
Liquidity Ratio	Cash/Sales	Negative
Profitability Ratio	Net Earnings / Total Assets	Negative
Cumulative assets' profitability	Retained Earnings/Total Assets	Negative
Coverage Ratio	EBITDA/Interest expenses	Negative
Activity Ratio	Operative Turnover of the firm (*Sales*)	Negative
Value of the innovative assets (patent value ratio)	Capitalized Patent Value Stock to Capitalized Patents Stock	Negative
patent productivity	Capitalized Patent Stock to Capitalized R&D personnel	Non-significant (when variable considered alone)
Innovation Measure Variable	***Equity Ratio* Patent productivity***	**Negative**

1.6. The role of innovation in the credit ratings of mature/listed firms

In respect to the *high-tech sector*, Zhang, He and Zhou (2013) analyzing a dataset of china's listed firms, argued that financial ratios like: *current ratio*, *ROE, total assets turnover ratio* and *accounts receivable turnover*, have a significant impact on high tech firms' default probability, while firms' region seemed to have a lower effect. They also argued that the *independent innovation ability* of firms had a strong relationship with its credit risk, since higher levels of this factor led to a reduction in firms' credit risk.

To analyze the perception of *rating agencies* for *innovation*, Al-Najjar and Elgammal (2013) studied a sample of mature firms rated by *S&P*. They supported that the factors presented on Table 7 affect the firms' credit score. Moreover, it was indicated that agencies aim on a long-term credit risk assessment and that credit ratings can be viewed within the context of *capital structure*. For *innovation* factor however, there is an *internal optimal* for every firm, meaning that a firm with higher levels of *R&D intensity* than its specific optimal level, has lower credit scores.

Table 7. Factors affecting mature firms' S&P credit rating (Al-Najjar and Elgammal, 2013)

Factor	Definition of Factor	Factor–Credit Rating Relationship
Growth opportunities	market to book ratio	Positive
Business risk	standard deviation of ROA	Negative
Profitability	net income to equity	Positive
Firm's size	total assets	Positive
Leverage	total debt to total assets	Negative
Firm's innovation	***R&D expenses to total sales (R&D intensity)***	***Positive*** ****until turning point***

For *listed* firms, Griffin, Hong and Ryou (2018) indicated that *innovative efficiency* (IE) expressed as granted patents to R&D expenses and patent citations to R&D expenses, is *strongly* and *negatively* correlated with the *future cost of credit*. They supported that credit rating agencies have a *lagged response* to the *IE information* and due to this lagged response innovative firms suffer a higher cost of debt (in short-term) than their credit-risk assessment would propose. Moreover, the study argued that future ratings of innovative firms improve with lower default probability, lower market competition and higher quality of management. In addition, the *quality of accounting data* strengthens the present IE-future rating relationship (for the next five fiscal years).

1.7. Risks of VC-backed firms

By analyzing the IPO events of various firms, Bamford and Douthett (2012) study the type of risks that VCs perceive, are willing to take and trying to mitigate. Specifically, they focus on the response of VCs to *firm-specific* risks. They argue that VCs are risk-affine in refers to risks associated with *operating profit margin* and *long run sales generation* (Table 8), due to the their capability to manage them. By contrast, VCs aren't willing to take risks related to *operational financing*, addressing the importance of company's daily cash flow as a risk factor. Bamford and Douthett, also support, that VC-backed companies achieve better financial performance for the fiscal years after the IPO, compare to non VC-backed companies, validated by the observed changes in companies' *Altman Z-score* in pre- and post- IPO years.

Table 8. Firm-specific risks for VC-backed firms (Bamford and Douthett, 2012)

Risk Factor	Risk Definition
operating profit margin	risks arising from supplier costs and the role of competitors in company's product pricing process
long run sales generation	risks arising from company's inability to establish a steady stream of customers
operational financing	risks arising from company's inability to produce cash flows from operations

The Altman Z-score is a model computed on the basis of the firm's working capital, earnings, equity, and sales (Altman and Sabato, 2005).

Besides the IPO time, the categorization of risk that VC-backed firm's face is crucial for their creditworthiness assessment. Proksch et al. (2016), provide in their model a framework for the different type of risks that presented on the relevant literature (Table 9). In accordance to Proksch et al., the most significant factor, among those presented in Table 10, to mitigate the *failure risk* of a portfolio company, are the *experience* and the *skills* of the *investment manager*. This specific factor was measured by the *working experience*, the *founding experience*, the *technology expertise* and the *network size* of the investment manager.

Table 9. Type of risks faced by VC-backed firms (Proksch et al., 2016)

Type of risk	Risk Definition
Liquidity/financial risk	Probability that the firm will become illiquid or bankrupt
Agency risk	Adverse selection and moral hazard between entrepreneurs and VCs
Technology risk	Refers to technical problems presented in the product development
Market risk	Risks associated with the commercialization of the firm’s product
Human resources risk	Risks regarding the quality of firms managerial skills
Internationalization risk	Risks arising when the operating domain of the new venture is international
Macro risk/volatility	Refers to macroeconomic factors. It includes risks like inflation risk, cyclical risk, interest rate risk and foreign exchange rate risk.
Failure risk	Includes the liquidity risk, market risk, human resources risk and technology risk, mentioned above

Table 10. Mechanisms used by VCs to mitigate the risks faced by VC-backed firms (Proksch et al., 2016)

Type of risk	Mechanisms to mitigate the Risk
Liquidity/financial risk	VCs invest in high-tech - early stage ventures or/and increase the syndication size
Agency risk	Information asymmetries are faced by, contracting, staged investments (milestone or round financing) and involvement of VCs in firm’s board
Technology risk	Investment managers with industry experience and applying of specific due diligence for technology
Market risk	Due diligences focusing in market risk
Human resources risk	Investing in strong management teams
Internationalization risk	Adjustment of syndication size, investment size, number of financing rounds
Macro risk	Adjustment of capital injection. High macro risk leads to fewer investments and lower investment sizes
Failure risk	Assessment of new ventures, governance mechanisms, contracts (e.g. liquidation preference, cumulative dividends, anti-dilution rights), investment manager´s experience and skills and management support

The classification of risks faced by VCs is a helpful tool for the proposed rating framework. However, should be noticed that there is interrelationship between the different risk types. As Tennert, Lambert and Burghof (2018) suggest, the *macro* and *market* risks are forming the *agency* risks (VC–entrepreneur relationship).

Referring to *syndication* as method to mitigate the risks presented in VC industry, the differentiation among VC investors should be mentioned. Each category of VCs follows a specific policy and strategy, sets different goals (e.g. expected returns) and mitigates different risks. Specifically, *bank-affiliated* VCs prefer to invest in firms with low levels of financial risk as that described by the *Altman–Z score* and also firms that are backed by such VCs, present higher levels of *debt exposure (*financial debt over total sales) after the first financing round, compared to non-VC backed firms (Croce, D'Adda and Ughetto, 2014). Croce, D'Adda and Ughetto also suggest that this increase in debt may stem from the role of *bank-affiliated* VCs as intermediaries between banks and startups or their signaling effect to the loan market. Therefore, in case of syndication among *independent VCs*, that will focus on the selection and the monitoring of the venture and *bank-affiliated* VCs, that will provide valuable *network* of contacts, the level in which this syndication utilizes these complimentary skills should be assessed by the rating framework. Although syndication of investors is a measure to mitigate the risks of a venture, such as financial and agency risks, attention should be given to the *syndication size*. As Tennert, Lambert and Burghof (2018) argued, that *moral hazard risks* and *syndication size* curve is U-shaped, for ventures in high-risk environments.

Generally, identifying and evaluating the methods used by VCs to mitigate the risks they faced, are significant studies for the assessment of the startup's credit risk. Venture Lenders should understand VCs investment strategies (e.g. capitalize on the risk-return relation) and their impact on firm's credit risk.

1.8. Firm valuation & PME methods as an indicator of VC quality

The study of the *VCs evaluation approaches*, the impact of *VC financing* on portfolio firms and the analysis of *VC's investments performance*, could be useful tools for the establishment of the CRF.

The analysis of *startup's valuation* is important for its creditworthiness assessment. Existed valuation methods such as, *use of multiples* and *cost approaches*, don't indicate the *intrinsic value* of the venture, while *venture capital method, real option analysis* and *discount cash flow analysis* (DCF) aren't able to *incorporate risk* into the *discount rate* properly (van de Schootbrugge and Wong, 2013). Since *venture debt* is always used in *tandem* with *equity*, startup's valuation is useful. Festel, Wuermseher and Cattaneo (2013) proposed a framework for the adjustment of *beta* *coefficient* used for *valuation of early stage ventures*. The specific adjustment was based on the startups' business plan data (Fig.11). The framework's methodology started with the beta adjustment for every high tech startup analyzed. Consequently, with the use of *Capital Asset Pricing Model* (CAPM) the *required return (discount rate)* was calculated and used as an input parameter in *DCF analysis* for startup's valuation. In particular, the basic coefficient initially used was equal to 6.4 and derived by the use of CAPM with a 4.126% *free interest rate*, a *market risk premium* of 5.5% and a *high rate of return*, expected by VCs in early stages, equal to 39.5%. *Fig.*11 and *Fig.*12 could be a guide for the adjustment of the high discount rates considered.

Organisation	Competences of the management team	Management team with major flaws	**Management team with some flaws**	Management team is complete	Management team is complete and competent	Management team is complete and very competent
	Headquarters location	Headquarters location problematic	Headquarters location can be improved	Headquarters location is fine	**Headquarters location has advantages**	Headquarters location has many advantages
	Competences of advisory board	Very low level of competences of advisory board/ consultants	Low level of competences of advisory board/ consultants	**Moderate level of competences of advisory board/ consultants**	High level of competences of advisory board/ consultants	Very high level of competences of advisory board/ consultants
	Process efficiency	Process inefficient	Process not very efficient	**Process efficient**	Process very efficient	Process exceptionally efficient
Finances	Sales plan	Sales plan unjustifiable	**Sales plan difficult to justify**	Sales plan justifiable	Sales plan conservative	Sales plan very conservative
	Costs plan	**Costs plan unjustifiable**	Costs plan difficult to justify	Costs plan justifiable	Costs plan conservative	Costs plan very conservative
	Profitability	Fundamentally low profitability	Risk of low profitability	**Average profitability**	Currently high profitability	Fundamentally high profitability
	Liquidity plan	**Financial resources for next year are not secured**	Financial resources for next year are secured	Financial resources for next 2 years are secured	Financial resources for next 3 years are secured	Financial resources for next 4 years are secured

Fig. 12: Adjustment of the beta coefficient for biotech & medtech startups based on business plan data (ii) (Festel, Wuermseher and Cattaneo, 2013)

As it is denoted, for the proposed CRF, the analysis of the *risks* and *returns* of *VC funds* invested in the startup is essential. For this purpose the assessment of VC's investment with the usage of *Public Market Equivalent* analysis (PME) is a suitable approach, since PME is commonly applied by the Private Equity Industry to evaluate the performance of a Private Equity Fund against a *Public Market Index*. According to the Private Markets Due Diligence Survey (eVestment, 2018) the most popular PME methods used by various investors and consultants are presented on **Fig. 12**.

Category	Subcategory	Adjustment of the beta coefficient				
		+1	+0,5	0	-0.5	-1
Technology	Maturity of technology	Technology still in initial experimental phase	**Technology successful on a laboratory scale**	Technology successful in pilot plant	Technology successful in demo plant	Technology successful in technical application
	Advantages compared to competitive technologies	No advantages identified	Advantages not clearly identifiable	Costs or quality advantages identifiable	**Costs and quality advantages identifiable**	Significant costs and quality advantages identifiable
	Reputation of scientist	**No reputation**	Poor reputation	Moderate reputation	Good reputation	Very good reputation
	Patent protection	No patent application	**First patent application filed**	Basic patent close to being granted	Basic patent granted	Extensive portfolio of granted patents
Products	Product benefits	Product benefits not identifiable	**Product benefits not clearly identifiable**	Product benefits clearly identifiable	Product benefits confirmed by first clients	Product benefits confirmed by numerous clients
	Unique selling proposition	Unique selling proposition not identifiable	**Unique selling proposition not clearly identifiable**	Unique selling proposition clearly identifiable	Unique selling proposition confirmed by first clients	Unique selling proposition confirmed by numerous clients
	Scalability	Very low scalability	**Low scalability**	Moderate scalability	High scalability	Very high scalability
	Competition	Currently strong competition	**Potentially strong competition**	Moderate competition	Low competition	Long-term low competition
Implementation	Business plan	**Business plan unjustifiable**	Business plan with open questions	Business plan plausible	Business plan occasionally proven	Business plan frequently proven
	Technical development plan	Technical development plan unjustifiable	**Technical development plan difficult to justify**	Technical development plan justifiable	Technical development plan likely to be feasible	Technical development plan very likely to be feasible
	Marketing plan	Marketing plan unjustifiable	Marketing plan difficult to justify	**Marketing plan justifiable**	Marketing plan likely to be feasible	Marketing plan very likely to be feasible
	Business development plan	Business development plan unjustifiable	Business development plan difficult to justify	**Business development plan justifiable**	Business development plan likely to be feasible	Business development plan very likely to be feasible

Fig. 11: Adjustment of the beta coefficient for biotech& medtech startups based on business plan data (i) (Festel, Wuermseher and Cattaneo, 2013)

The *Kaplan Schoar PME* method (KS-PME) compares the *LPs' investments* in a *VC fund* to investments in the *S&P 500 index*. Specifically, the method applied by investing (or discounting) all cash outflows of the VC fund at the total return to the S&P 500 index and comparing the value resulted to the value of the cash inflows (all net of fees) to the fund invested (discounted) using the total return to the S&P 500 index. KS- PME above 1 indicates that the VC fund outperform the index, while PME below 1 indicates that the public index is a better investment than the fund (Kaplan and Schoar, 2005).

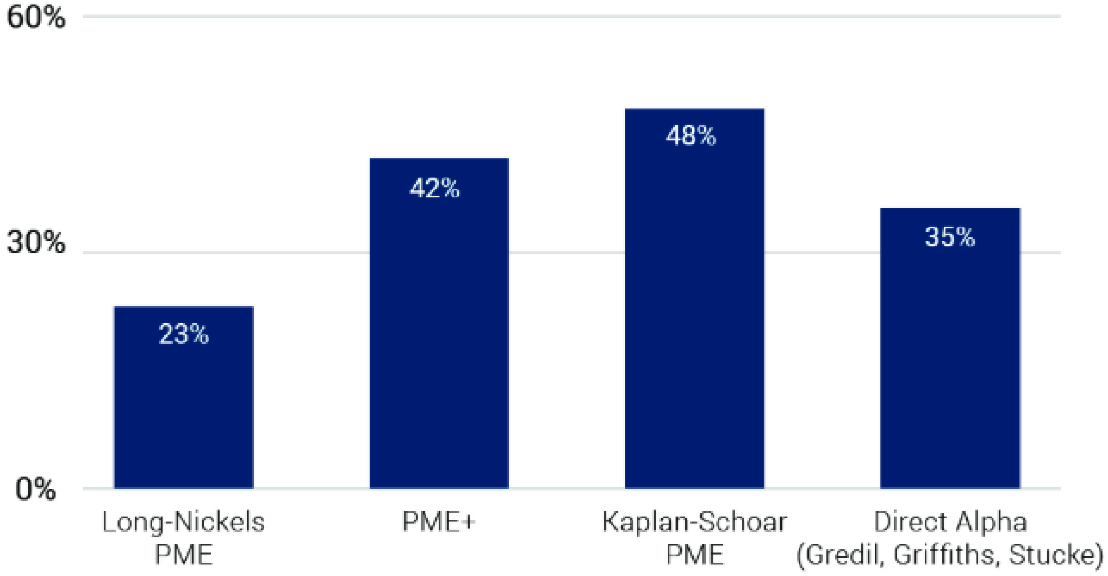

Fig 12: PME methods used by various investors and consultants (eVestment, 2018)

However, KS-PME doesn't correctly adjust for the extent to which *high-beta assets* (far from 1) mechanically outperform a public market index in times of rising public equity markets (KORTEWEG and NAGEL, 2016). Relaxing the *stochastic discount factor (SDF) restrictions* applied in the KS-PME method, in order for the SDF to accurately reflect *risk-free rates* and *returns* of public equity markets during the sample period, KORTEWEG and NAGEL proposed the *generalized PME method* (GPME).

The estimation of VC fund's performance invested on the firm, based on PME could provide a valuable insight for the credit rating of a portfolio firm. CRF utilizes the PME methods, as a proxy of *VC quality*. In particular, PME method could be applied for firm's lead investors.

Risk adjusting the returns of VC funds' investments and analyzing the funds' performance could be supportive for the proposed CRF. However some factors should be considered:

- In cases of *high-quality fund managers*, the expected correlation that *more diversified* VC funds *outperform* the *less diversified* ones in respect to VC industry, may lead managers to endogenously choose *riskier investments*

(Buchner, Mohamed and Schwienbacher, 2017). A rating methodology for startups, should detect the *determinants of VCs investing* and *levels of risks* taken *specifically* for *the firm to be rated*.

- The relationship *of VC funds performance – startups performance*. Analysis of the impact of VCs' investment on firm's performance (growth, innovation, etc.) is a necessary tool for firms' rating. Under this scope, distinguish between *selection* and *monitoring* effect of VCs investments may also be supportive towards this direction.
- The study of the *interrelationship* among GPs, LPs and entrepreneurs with respect to its impact *on risks assessment* and on *VC deals pricing*.
- The *cost of equity estimation*. Specifically, the levels for witch founders and partially diversified VCs investors compensate for the *idiosyncratic (diversifiable) risk.*
- VC *syndication frictions* and its impact on firm's probability of financial distress. Specifically, the different investment horizons among VCs, with respect to fund cycles, the asymmetric information among investors (insiders & outsiders) and also the different follow-on financing incentives of VCs based on their fund sizes should be considered (Nanda and Rhodes-Kropf, 2017). Regarding the latter factor for example, in case that a startup is backed by a large VC fund the choice of this fund not to follow-on with the investment in subsequent round may have a highly negative signal to capital markets. Additionally, the existence of contracts that mitigate syndication frictions should also be evaluated.
- The facts that VC returns are highly skewed (total returns come from a small fraction of their investments) and that VCs invest in startups with high idiosyncratic volatility and load heavily on aggregate changes in idiosyncratic volatility (Peters, 2017).
- Generally, VCs are focusing on firm's growth while lenders focus on the downside risk.

In the framework of rationalizing the *discount rates* used by VCs and *estimating* the *cost of capital*, Bhagat (2014) argued that the high-discount rates can be explained by the *probability* that the venture will achieve a *successful exit* (IPO or acquisition). Considering 2 investment stages for a venture project (A: market approach & technology development, B: commercial production & marketing decisions) and applying the zero-profit condition, for VC industry, in the long-run equilibrium, the research provide the indexes of Fig.13 and Fig14.

$p_A \rightarrow$ $r_A \downarrow$	0.30	0.40	0.50	0.60	0.70
0.05	0.92	0.66	0.48	0.36	0.25
0.10	0.96	0.70	0.52	0.39	0.28
0.15	1.00	0.74	0.55	0.42	0.31
0.20	1.05	0.77	0.59	0.45	0.34
0.25	1.09	0.81	0.62	0.48	0.37

Fig.13: Index of Discount Rates based on successful exit probability (i). With p_A, the probability of successful exit and r_A, the discount rate (due to ventures' systematic risk) given that the venture will succeed. A risk-free rate of 5 % used **(**Bhagat, 2014).

$p_B \rightarrow$ $r_B \downarrow$	0.60	0.70	0.80	0.90	0.95
0.05	0.75	0.50	0.31	0.17	0.11
0.10	0.83	0.57	0.38	0.22	0.16
0.15	0.92	0.64	0.44	0.28	0.21
0.20	1.00	0.71	0.50	0.33	0.26
0.25	1.08	0.79	0.56	0.39	0.32

Fig.14: Index of Discount Rates based on successful exit probability (ii). With pa<pb **(**Bhagat, 2014).

Given the *sensitivity of Discount Rates to exit probability*, the significance of startups' potential exit for the estimation of cost of capital and future cash-flows and for its valuation should be considered. The credit rating framework for VC-backed early-stage firms should *assess* and *incorporate* the firm's *capability for a successful exit*, since a potential exit could impact both the firms' *creditworthiness* and also the *incentives* for venture lending (due to warrants).

Regarding the assessment of VC-backed firms' strategies to *exit* through acquisitions, the credit rating process could analyze the M&A transactions data (Fig. 15). Particularly, the firms that acquire startups prefer to buy local companies, while geographical distance is highly important in cross-border M&A transaction. Moreover *acquirers* (both from US & Europe) tend to *choose younger startups*, indicating that older firms have lower probabilities of being acquired.

Additionally, in respect to exits through *IPO*, the proposed CRF could analyze the *VC-backed IPO Statistics indexes*. Specifically, technology IPOs data and IPOs indexes by region and industry could be analyzed.

Startups age at the time of acquisition	European startups No.	European startups (%)	US startups No.	US startups (%)	Total No.	Total (%)
0-5	442	36	1993	44	2435	43
of which:						
– 0-1	*65*	*5*	*263*	*6*	*328*	*6*
– 2-3	*181*	*15*	*955*	*21*	*1136*	*20*
– 4-5	*196*	*16*	*775*	*17*	*971*	*17*
6-10	363	29	1199	27	1562	27
11-16	304	25	970	21	1274	22
16-21	123	10	350	8	473	8
Total	1232	100	4512	100	5744	100

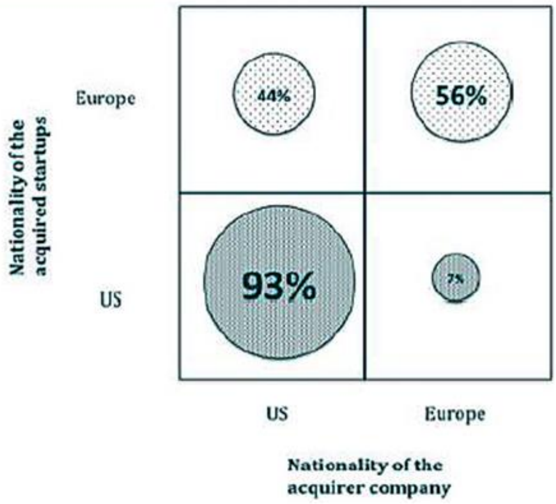

Fig.15: Startups' age at the time of M&A transaction and comparison sample period (2012-16) (Pisoni and Onetti, 2018). Startup exits: domestic vs cross-border acquirers

1.9. Mature firms' & Startups' relationship with Business Cycles

Rating agencies attach importance to *industry risk* and the *patterns of business cycle* for the assessment of issuer's business risk. For *the S&P corporate rating methodology* in particular, the assessment of the industry risk has a highly significant impact on setting the upper limit of the debt rating category. Cyclicality is incorporated on business risk assesment and rating agencies are analyzing the firm's expected levels of deviation from its rating category in a full business cycle (includes a single boom and contraction in sequence). The ideal approach is the *rating through* *the cycle* (Fig.16), since it is obvious that giving a high rating to a firm that its performance level is expected to be temporary is a wrong approach. However, this approach it's difficult to applied due to the bellow factors (S&P CORPORATE RATINGS CRITERIA, 2013):

- The prediction of the cyclical pattern.
- The firm's preventive action plan for the predicted business cycle (e.g. conservative strategy due to an expected downturn).
- Although generally business cycles are marked by fluctuations in aggregate economic activity, there are different types of cycles such as demand driven or supply-driven, while some cycles could be industry-specific. The interrelationship of these cycles is a complex process.
- Distinguish between cyclical factors and changes in industry factors (new competitors, shifts in customer preferences, technological changes, etc.) is a challenging task.
- Rating agencies should also consider the capital providers' perceptions for the firm performance-business cycle relationship.

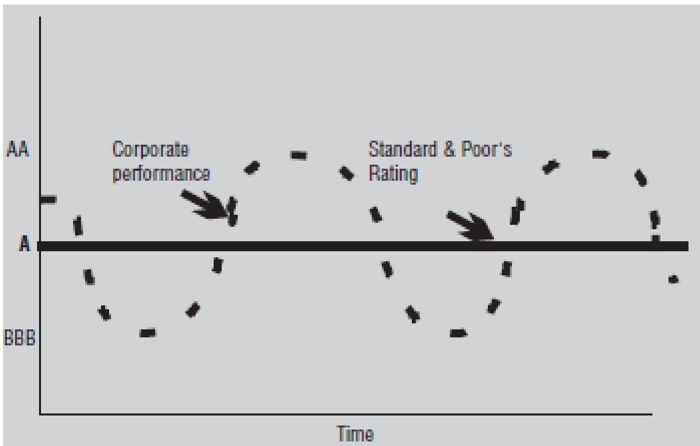

Fig16: Relationship of ratings and cycles: rating through the cycle approach (S&P CORPORATE RATINGS CRITERIA, 2013)

Some industries however, present a rating-cycle relationship where the *rating* is *adjusted* with the *phases of the cycle* (Fig.17). As denoted by the S&P guide the *cyclical factors-rating stability sensitivity* changes from different *rating categories.*

Specifically, a cyclical upturn for a non-investment grade firm could lead to an upgrade of firm's rating category.

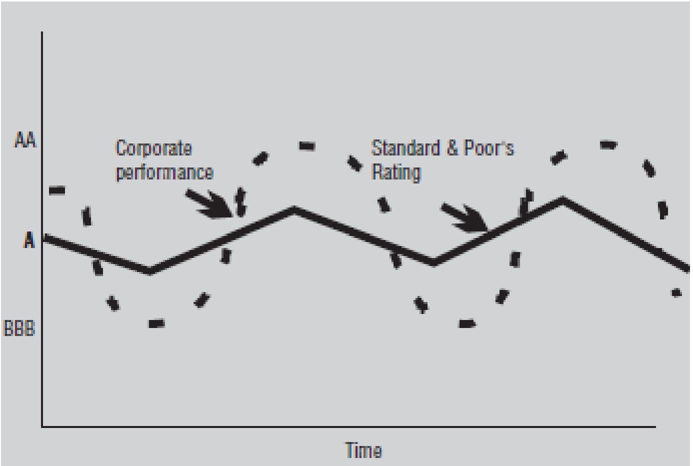

Fig.17: Relationship of ratings and cycles: adjustment approach (S&P CORPORATE RATINGS CRITERIA, 2013).

In regards to *startups-business cycle* relationship on *industry level*, Konon, Fritsch and Kritikos (2018) classified startups in 4 categories based on the framework presented on Table 11.

Table 11.Startups classification for the analysis of startups-business cycle relationship (Konon, Fritsch and Kritikos, 2018)

Innovation Factor	**Expectation of Small Scale Business**	**Expectation of Large Scale Business**
Innovative	*Knowledge intensive services, technology oriented services etc.*	*High-tech & technologically advanced manufacturing*
Non-Innovative	*Consumer oriented services , trade etc.*	*Energy, non-innovative Manufacturing etc.*

Based on data from German region and the above classification, the results for the *startups-business cycles relationship* are (Konon, Fritsch and Kritikos, 2018):

- *Counter-cyclical effects* of the *business cycle* on *entries to market*, since more startups are founded when GDP is low or unemployment is high. Specifically, for innovative firms expected to entry small scale industries, an economic downward movement may lead to higher market entries.

- A Market entry for a startup with expected large-scale business are mainly affected by changes in unemployment, in contrast with a market entry in small-scale industries which is affected by changes in GDP.
- Economic periods with high GDP might not be relevant to startups' market entries.
- Both startups with higher levels of innovation and those with lower levels response counter-cyclically in contractions.

1.10. Cyclicality of VC activity

Regarding to the *VC activity-Cyclicality* relationship, *entry to VC Market* and *fund performance* are *procyclical*, nonetheless, well established VCs funds are less sensitive to cycles than new funds (Kaplan and schoar, 2005). Moreover, *distributions* and *calls* both have a *procyclical* systematic component, with *distributions* being more *sensitive* to *cycles* compared to calls (Robinson and Sensoy, 2011). In terms of the uncertainty that follows VCs investments, the *risk premium* or the *effective discount rate* on *risky assets* are *high* in periods of *contraction* and *low* in periods of *expansion* (Hoffmann, 2018).

For the *assessment of VC-backed firms' creditworthiness*, the analysis of both *startups-cyclicality* and *VC activity-Cyclicality* relationships could be useful.

Analyzing the VC strategies in the framework of VC backed firms' credibility assessment, the effect of *investment cycles* should be considered. Particularly, in *boom periods* VC *syndicates* use to be *smaller* in size, since sufficient funding capital for the *subsequent financing* round is assumed and the involvement of current insiders investors for the next round is not a significant matter (Nanda and Rhodes-Kropf, 2013). In contrast on *cold markets* the participation of early stage investors on the follow-on financing round is substantial. Moreover, in *cold market* periods VCs *prioritize among their portfolio firms* and on *syndication level* there could be conflicts among investors' priorities for a specific firm that may impact its ability to secure sufficient funding. Due to this phenomenon firms that considered viable may face a financial distress (Nanda and Rhodes-Kropf, 2017). Since venture loan repayment is based on startup's ability to secure *follow-on financing* the syndication response to market cycles is a significant factor.

1.11. VC industry trends & VC/PE country attractiveness index

On country level and given that VD repayment is based on next equity round, VLs could utilize the *VC/PE country attractiveness index* (Fig.18).

For the CRF, the analysis of *VC industry trends* is highly significant. Lenders could utilize the bellow indicators used on the Silicon Valley VC survey by the Fenwick & West LLP:

- *IPO activity:* number of IPOs, the time to IPO and the raised amount.
- *M&A activity*: number of M&A deals and value of M&A deals.
- *VC investment*: deal-flow & the total dollar value of the financings.
- *Venture Capital Fundraising*: fund count and raised capital.

Since venture loans are repaid through the next equity round, CRF could assess the firm's ability to achieve *high valuation* in the future. Future *down-rounds* or *flat rounds* not only affect the repayment process but also the potential upside proceeds from the equity kicker (warrants). Lenders could monitor the *price (per share) at which firms raise funds* and also could analyze the *% of down-rounds* by *industry* and by *Series*, for the relevant VC Markets.

Referring to firms headquartered in Silicon Valley, Series B, which is a significant round for early stage firms, achieved the strongest valuation results in Q3 2018. In respect to sectors, the life sciences firms presented the strongest valuation results (Fig.19, Fig.20).

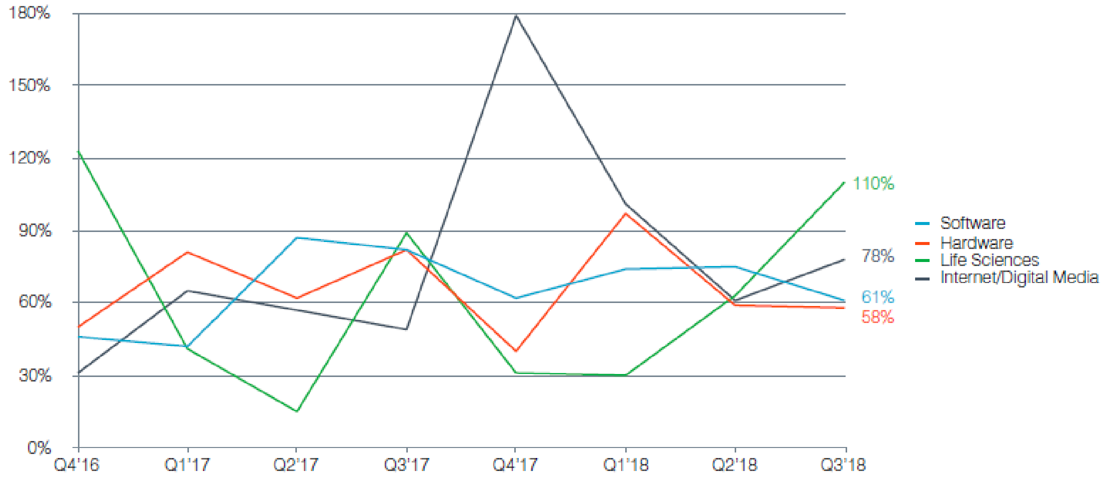

Fig.19: Average change (%) between the price (per share) at which firms raised funds in a quarter and the price (per share) at which such firms raised funds in their prior equity round, by sector. Findings from Silicon Valley Venture Capital Survey (Clarfield Hess, Leahy and Tran, 2018).

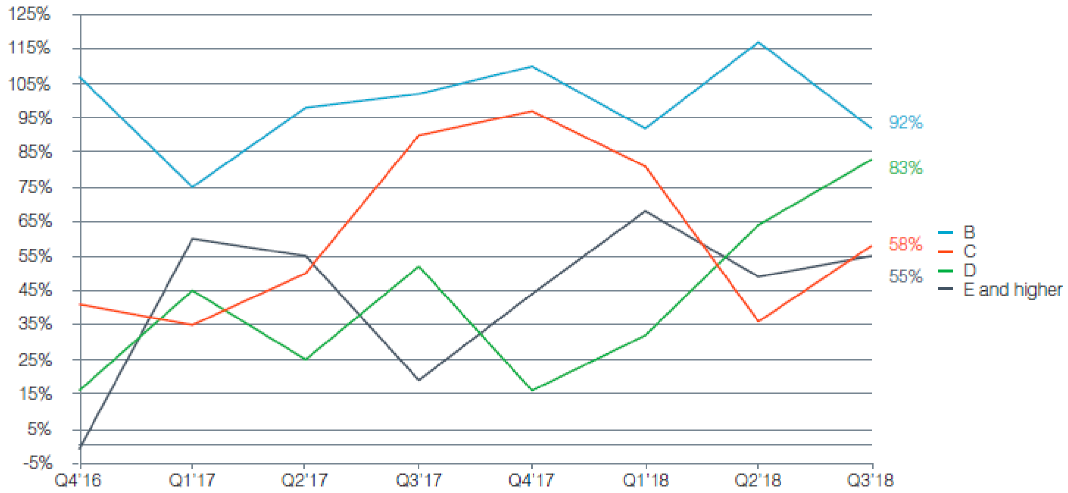

Fig.20: Average change (%) between the price (per share) at which firms raised funds in a quarter and the price (per share) at which such firms raised funds in their prior equity round, by Series. Findings from Silicon Valley Venture Capital Survey (Clarfield Hess, Leahy and Tran, 2018).

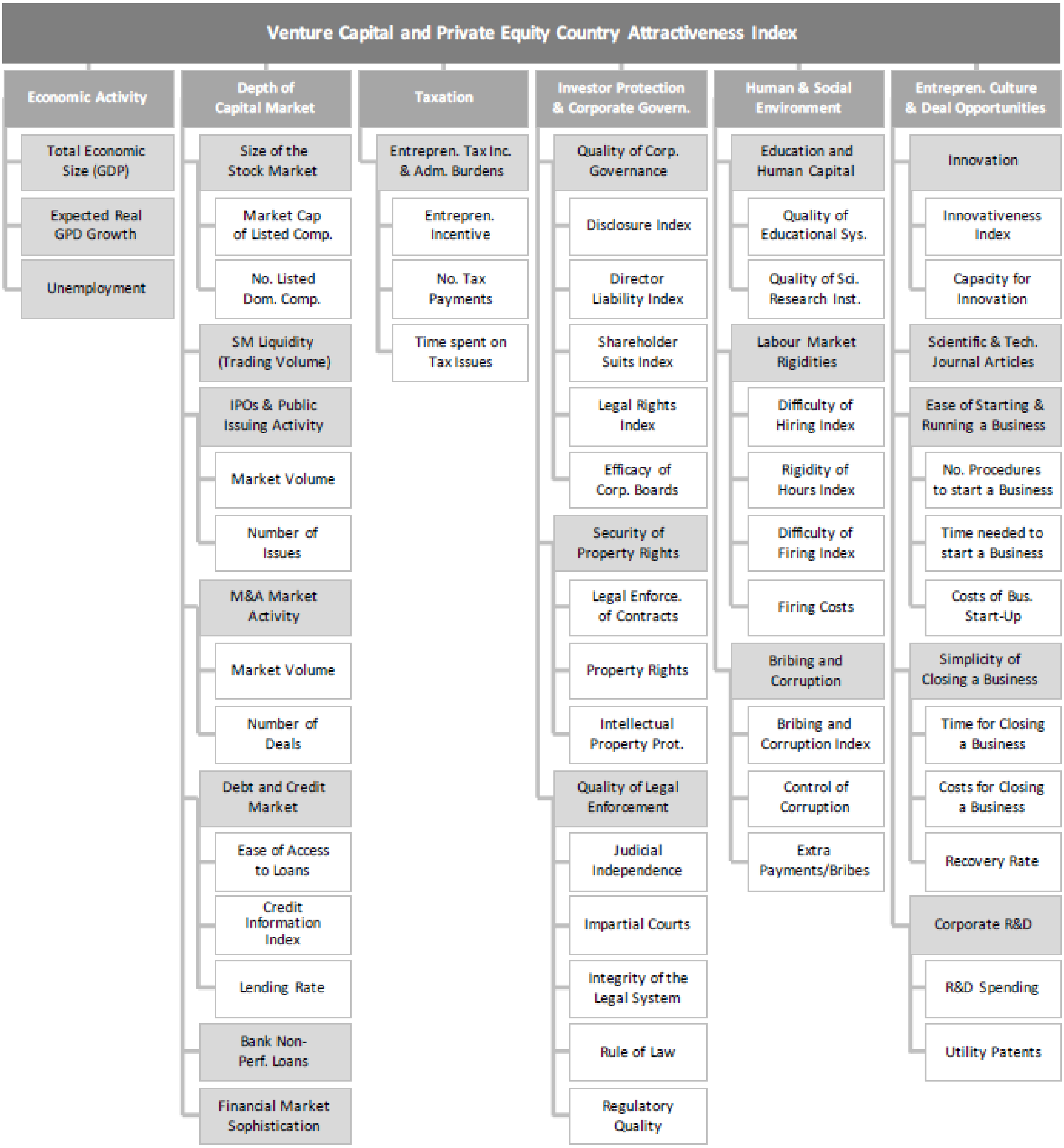

Fig.18: VC & PE country attractiveness index (Groh et al., 2018).

1.12. Startups financial constraints & follow-on financing

Since the repayment of venture loan is mostly based on the VCs' follow-on financing, the analysis of the index in which VCs alleviates the financial constraints of their portfolio firms, is a significant factor for the assessment of startups' creditworthiness.

The first problem needed to be addressed is the distinguish between *VC's certification*, meaning the signal of the portfolio firm to the capital markets due to the selection by the VC, and *VC's treatment effect*, which mainly refers to VC's capital injections and other skills that a VC provide to a firm. Another distinguish that should be made is the *stage* in which VC relaxes the firm's financial constraints, since a follow-on financing round indicates a stronger VC's certification than the initial around. By the time of a follow-on round the VC investors have more valuable information in regard to firm's characteristics and their investment choice provide a strong signal to the capital markets. Addressing for the above issues, Bertoni, Croce and Guerini (2015) supported that the *investment curve*, which expresses the relationship *capital investment - availability of internal capital*, is *U-shaped* and not linear, due to capital market imperfections (Fig.21). Moreover, they indicated that VC financing leads the investment curve to flatten, only after the follow-on financing round occurs. Additionally, it was supported that the size of capital invested by VCs has low impact on alleviation of firms' external financial constraints, while VC's certification has a high impact.

Based on those findings, the *proposed CRF* focuses on *VC's track record* in respect to *VC's commitment* for follow-on financing, the compliance with loan obligations and the previous relationships with lending institutions. Generally, an assessment criterion should be the *perception of capital markets* for the VC's quality.

Analyzing the staging investment, the optimal construct of the financial contracts and the levels of investor's financial commitment (e.g. milestones or round financing), Talmor and Cuny (2005) indicated the significance of the factors referred bellow: "the levels *of entrepreneurial* and *VC's effort* to increase firm's value", "the preference of VCs to *faster exits* (*liquidity preference*)" and "the *different* *expectations* of entrepreneurs and VCs regarding the success of *firm's new technology*".

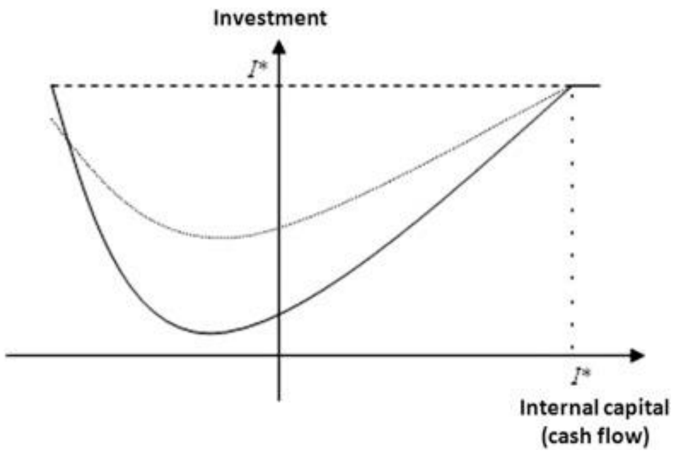

Fig.21: Investment curve for different levels of external financial constraints, with horizontal dashed line representing the first-best level of investment and black curve indicating higher level of external financial constraints compared to the dotted curve (Bertoni, Croce and Guerini, 2015).

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Setting the proposed rating framework, an analysis under the scope of *VC syndication* it's necessary. The ability of the syndication to overcome *moral hazard* and *adverse selection* problems should be assessed. In terms of *VC's commitment*, another assessment factor could be the levels of capital support by the smaller investors of the syndication, since this support leads to a lower demand for commitment by the lead investor.

1.13. Impact of VC financing on firms' performance, financial structure & access to debt

For a time period of 5 years after first financing round, Baeyens and Manigart (2006) analyzed the *financial structure* of VC-backed firms based on firm's *bankruptcy risk* (short-term) and *debt capacity*. For the latter, the *internally generated cash flow to total assets* (at year of subsequent financing) and the *lagged debt ratio* (at year before subsequent financing), measured as total debt relative to total assets, were used as indicators. While for the bankruptcy risk the *Ooghe-Joos-De Vos* model (for firms in Belgium) was used, although the model presents better performance for large companies and classical manufacturing industries (Ooghe, Balcaen and Camerlynck, 2002):

X1: Direction of the Financial Leverage
X2: (Accumulated Profits +Reserves)/(Total Liabilities less deferrals and accruals)
X3: Cash / Total Assets
X4: Overdue Short-Term Priority Debts
X5: Operational Net Working Capital/ Total Assets
X6: Net Operating Result / Working Assets
X7: Financial Debts (Short Term)/Short-term Liabilities
X8: Guaranteed Portion of Portion of Amounts Payable by Firm

As it is expected, VC backed firms financed through *bank debt* (2 years after initial VC investment) had *higher debt capacity*, achieving a median debt ratio of 71%, compared to those financed with equity. Moreover, VC backed firms had low or negative *internally generated cash flows*, with ratios equal to 5%, 10% and -10% for firms issued debt, equity from existing shareholders and equity from existing & new investors respectively. In regards to *bankruptcy risk*, the scores was 0.54 (relative low level) for firms issued debt, 0.64 (intermediate level) and 0.87 (highest level) for firms financed through existing investors and through existing & new investors respectively. Additionally, based on the assumption that private equity markets follows the performance of public markets, it was supported that *price/earnings* ratios and *long-term interest rate* referring to the 10-year benchmark government bond yield, affect the financial structure of VC-backed firms. Surprisingly in times of high price/earnings ratios VC-backed firms put debt financing as a first priority, since higher ratios implied *lower long-term interest rates*, making a favorable condition for issuing debt (Baeyens and Manigart, 2006).

The significance of *market conditions* (on country level) and *monetary policies decisions* should be considered for the access of startups to debt financing. As already denoted, *lower interest rates* may lead banks to a more "*risk taking*" approach, in terms of lending. However, incentives for lending to startups may impact their creditworthiness. Both interest rate cuts and rises increase the aggregate default rate in short-run, while higher rates lead to lower default rates in the longer run because they cause lower *target leverage* across startups (GONZÁLEZ-AGUADO and SUAREZ, 2015).

For a time-period of 4 years after VC initial financing/rejection, Bronzini, Caramellino and Magri (2017), studied the differences among VC-backed firms and those rejected by VCs in the due diligence phase (Italian firms). They supported that the VC-backed firms were more *innovative* (measured as number of patent applications) and achieved *faster growth* in size, in terms of *assets*, *labor costs* and *number of employees*. Additionally, VC-backed firms presented a *decrease* in their *leverage* and a significant *increase* in *equity*, indicating a stronger financial structure for those obtained VC financing. However, what should be focused on, is the decrease in profitability expressed as *EBITDA/Assets%*, (Fig.22) and the *lower credit ratings* of firms after VC financing. Moreover, VC backed firms had a *shorter debt maturity* and *higher cost of debt* (higher interest rates) compared to rejected firms, while VC financing *didn't guaranteed firms' survival* (Fig.22). Although firms had already weak credit ratings (ratings by Cerved, an Italian rating agency) before VC treatment the *additional decrease of ratings* after VC treatment is a significant issue. It is worth mentioned that at the time of VC financing the firms had *high leverage ratios*.

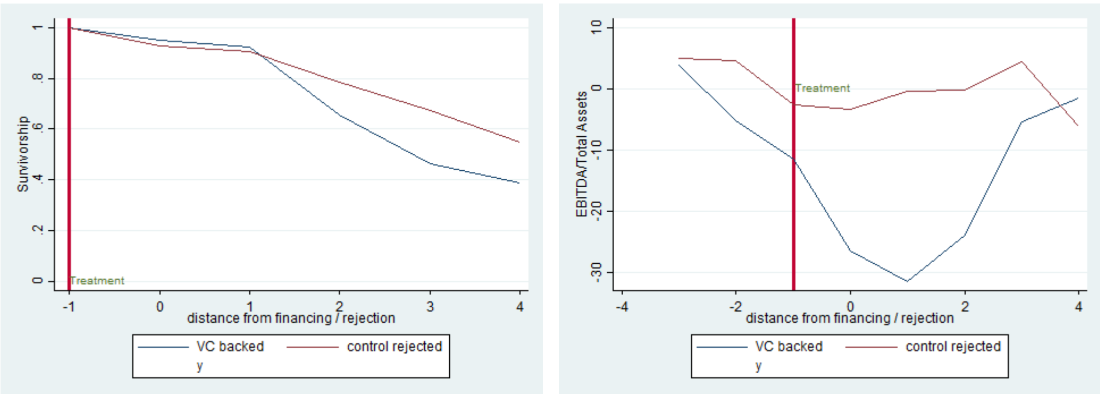

Fig.22: Survivorship and Profitability of VC-backed firms (blue line) and rejected firms (red line) (Bronzini, Caramellino and Magri, 2017)

Based on Fig.22, it is concluded that VC-backed firms' credibility could be assessed by their ability to *overcome fast the investment shock* improving firm's *debt* *capacity* in the future. Another indicator that can be evaluated is *the estimated time for an increase in sales* after the VC investment.

In regards to *VC financing - access to debt* relationship, the role of *VC-certification* is once again highly significant. Specifically, in the context of Spanish VC-backed firms, Balboa, Martí-Pellón and Tresierra-Tanaka (2011) argued that the *decrease in profitability* after initial investment didn't affect access to debt, while *tangibility* and *size* (larger firm access debt easier) were *less restrictive* factors to access debt. Consistent with relative literature, they supported, that VC-backed firms could rely on debt.

1.14. CRF & incentives of VC valuations

Since VD payments rely on startups ability to raise subsequent round of equity financing, the assessment of startup's creditworthiness should focus on the factors that lead to *higher private equity valuations*. In particular, Sievers, Mokwa and Keienburg (2013) indicated that VC valuations could be explained by both financial and non-financial data. Additionally, while only considering for hard factors to explain valuations, they supported that *R&D expenses, Revenues, Cash*, are *value-enhancing*. For soft facts it is worth mentioned that the existence of a *first customer* was *value-enhancing* too. The evidence that *R&D expenses* were *value- enhancing* (pre-IPO valuations) was also supported by Armstrong, Davila and Foster (2006), which shows that a rating methodology for startups should be aware for the significance of R&D expenses for firm's future performance.

As it is known early stage firms are usually characterized by negative cash flows and access to VD is not based on the traditional framework of *5 C's of Credit* (capacity, capital, collateral, conditions, and character) but instead is based on the cash of the subsequent equity round (de Rassenfosse and Fischer, 2016). However, the *overall creditworthiness* of a startup should *estimate* and *evaluate* the firm's *movement towards profits*. *Pre-revenue* startups could be assessed by the estimated time period needed to reach the *breakeven point*.

Since it is proposed that venture debt should be obtained soon after the VC investment and when the startup has still sufficient amount of cash (de Rassenfosse and Fischer, 2016), the *CRF* could focus on the *impact of VC treatment on firm's performance*.

1.15. VC financing & signal to debt markets

In respect to the *signal* of *startups* to banks in order for the former to secure *debt capital*, Aktekin, Dutta and Sohl (2017), categorized ventures' *signaling effects* in *intended* and *unintended*. Specifically, *unintended* signals referred to *emergent volatility* of *employees* and *revenues,* while *intended* referred to *diversities in startup's external capital* (VC, angel or private equity). They supported that higher the ability of the venture to rise external capital higher the banks incentive to lend, an expected result, compatible with the signal of VC certification to capital markets. Additionally, *emergent volatility of revenues* had a *deterrent effect* on banks' decision to lend to startups belong to *service sector*, while for startups in *manufacturing sector* negative effect of revenue volatility seemed to be *mitigated*. On the other hand, *volatilities in employment* had a negative impact on bank's lending decision for both sectors. Although the study referred to banks' incentives for provision of short-term debt its findings could help startups to access debt financing.

Based on the above findings and given that an increase in startup's employment reflects a positive sign to debt markets (Aktekin, Dutta and Sohl, 2017) and that large companies have easier access to loans (long-term) compare to smaller ones (Beck and Demirguc-Kunt, 2006), VC-backed firms should be monitored for their response on such *volatilities* in respect to their financial obligations (short-term & long-term).

1.16. CRF & the importance of startups' survival

Since lenders focus on the *downside risk*, an analysis of *R&D-firm survival* relationship could be useful for startups' credibility assessment. Generally, *R&D intensity-survival* relationship is *inverted-U shaped*, while firms that are R&D

intensive present *longer survival time* when operating in *concentrated* industries (Ugur, Trushin and Solomon, 2016). In regards to *startups* (Chinese firms) it was also supported an *inverted-U relationship* (Zhang and Mohnen, 2013), indicating the significance of the estimation of the turning point, for startups' valuation.

Referring to *survival* and *firms' stage*, the proposed CRF focus on the relevant factors presented on Fig.23.

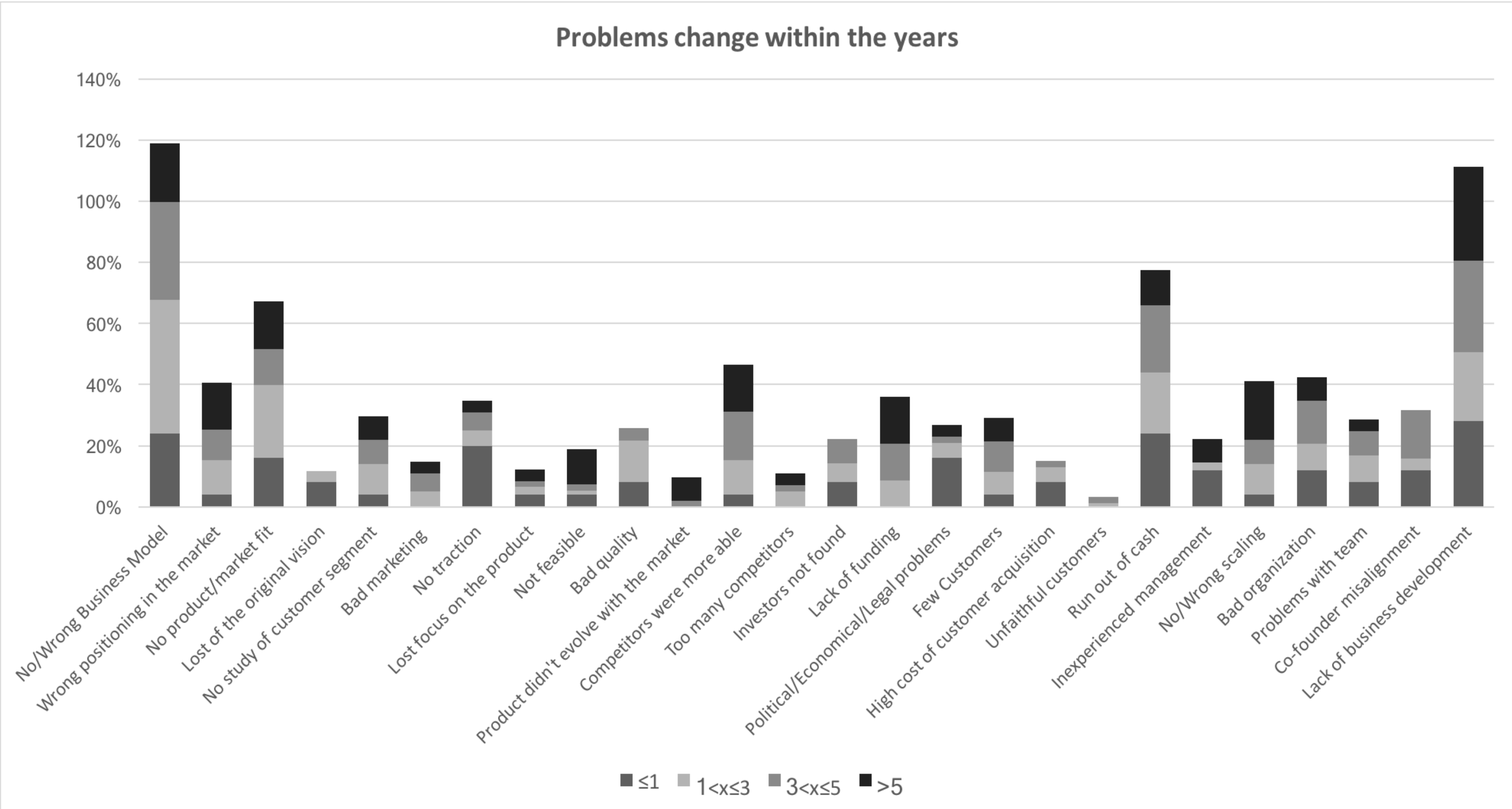

Fig.23: Factors of failure and high-tech startups' lifecycle (Cantamessa et al., 2018)

Focusing on the time-period from Series A to B, *product-market fit* and *work at scale efficiency* are significant factors. Based on SVB analysis for US tech firms, at the time Series B raised, firms have *revenue run-rates* between \$2.7M - \$5.3M and median *operating expenses* 120% higher than revenue (Moseley, 2018).

Since *accounting information* is crucial for rating agencies to analyze the innovation activities of mature firms and given that *high-tech startups* face more difficulties to *access* bank debt than *low-tech startups* (Brown et al., 2012), the ability of VCs to reduce the *information opacity* is highly important in the context of high tech startups. Moreover for high-tech startups, it is supported that banks rely *less* on credit ratings established by rating agencies (Brown et al., 2012). Since lenders focus on *downside* risk, VCs should also provide information relevant to this kind of risk. On the other hand, the CRF should focus on the relationship of firm's *innovation intensity* and firm's *survival*. Generally, the importance of innovation activities for the survival of high-tech startups is denoted on Fig.24.

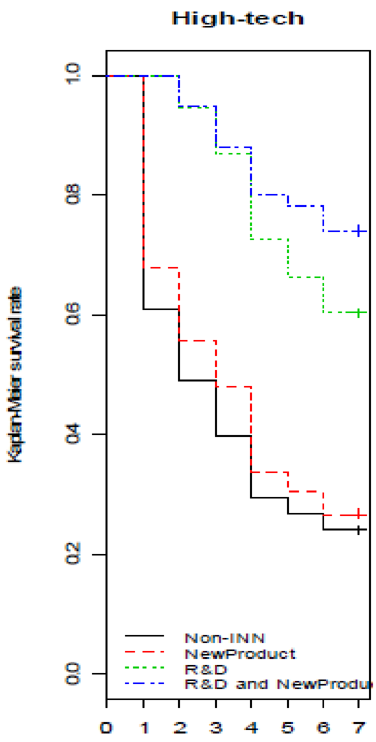

Fig.24: Kaplan-Meier survival rates for different levels of innovation. Graph presents 4 types of firms: firms with R&D & new product innovation intensity (blue line), firms with R&D only (green line), firms with new product innovation only (red line) and non-innovators (black line). Data collected from Chinese startups for the time-period of 2000-2006 (Zhang and Mohnen, 2013)

Since *information opacity* is an essential issue for the assessment of startups credibility and also qualitative analysis is important for such firms, startups ratings should focus on *soft data*. It is supported that high-tech startups tend to have a lower default rates when they are located closer to the lenders (banks), indicating the significance of *soft information* and *monitoring* (Kang, 2019).

1.17. Burn rates and firm's failure

Given that *venture loans* shouldn't be used when *burn rate is high*, while obtaining venture loan increases burn rate and high burn rates could have negative impact on pre-money valuations, the *estimation of startups' optimal burn rate* could be valuable.

Berman and Hernandez (2017) argued that the *normalized burn rate*, expressed as spending per employee, is a better indicator to estimate the probability of failure, compared to traditional burn rate. Moreover, they supported that the *normalized burn rate-probability of firm failure* relationship is *U-shaped*, while most startups spend less than the optimum spending (Fig.25). Additionally, they indicate that *entrepreneurs' education* and *work experience* are associated with optimum spending. The *CRF* utilizes the above analytical model, focusing on firm's ability to operate close to the *optimal normalized burn rate* and the contribution of VCs' managerial skills towards this direction.

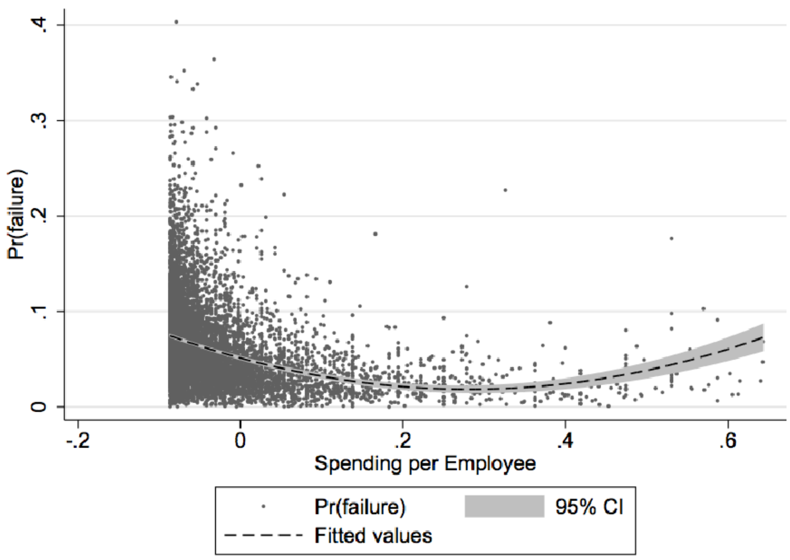

Fig.25: Relationship of normalized burn rate and probability of firm failure **(**Berman and Hernandez, 2017)

1.18. The role of intangible Assets for the proposed CRF

IP valuation is highly significant for the process of startups' creditworthiness assessment, since it is connected with both *collateralization* and *firm's value*. The taxonomy of Intangible Assets is presented on Fig.26. Similarly to tangible assets IP can be sold, mortgaged or disposed.

Given that startups have many intangible and few tangible assets, while internally generated intangible assets are not reflected in the financial statements, the IP valuation is challenging. Typically, in early stage investments, VCs use *market-based* and *cost approaches* for the valuation (IP Valuation Manual: A Preliminary Guide, 2018).

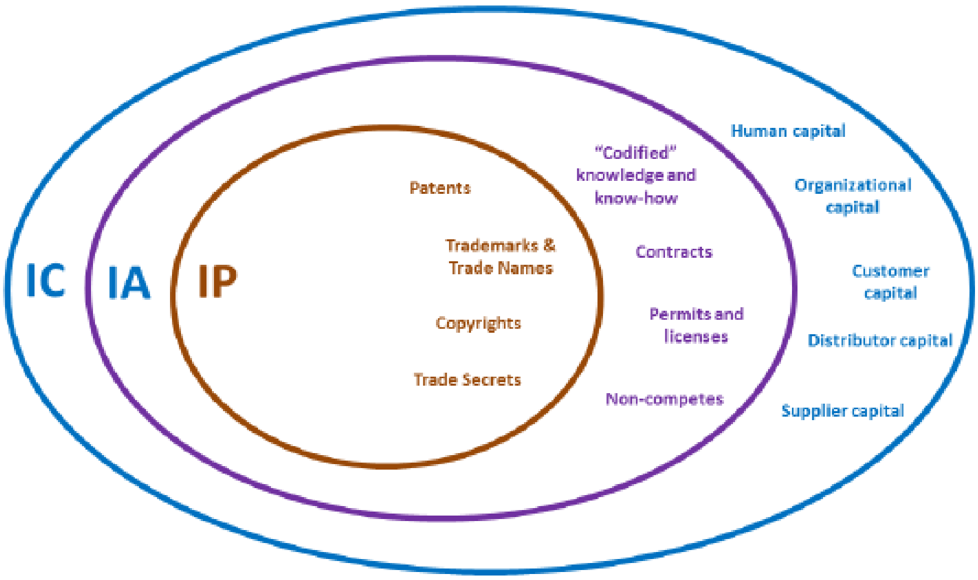

Fig.26: Taxonomy of Intangible Assets: Intellectual Property (IP) Intellectual Assets (IA), Intellectual Capital (IC) (Smith, Parr and Smith, 2001)

Concerning startups' access to debt, *customer-related* intangible assets should be evaluated. Specifically, there should be a focus on the efficient usage of *production backlogs* and the evaluation of *customer lists* or *customer contracts and the related customer relationships.*

One crucial issue is that venture lenders focus on the *liquidation value* of the asset and generally have a different perspective for valuations compared to VCs.

In regards to access to VD, as shown in Fig.7, *trademarks* are quite important. Trademarks could be used as *collateral* but there are also connected with firm's *reputation*. So, trademarks could be valuable for both *loan recovery* and firm's *creditworthiness*.

Referring to CRF, and the use of *patents* as *collateral*, the study of Hesse, Lutz and Talmor (2015) argued that the existence of at least one *granted* or *pending* patent has a *negative* impact on the cost of VD (both on credit spread and warrant coverage). However, this relationship is strong only for *early stage* startups, since patents granted in later stages don't have the quality signal to debt markets (Fig.27). These findings could help the access of *early stage* firms to VD, since startups that have pending patent seems to lower the cost of debt, so the proposed *recovery rating* could also *positively* assess the existence of *pending* patents.

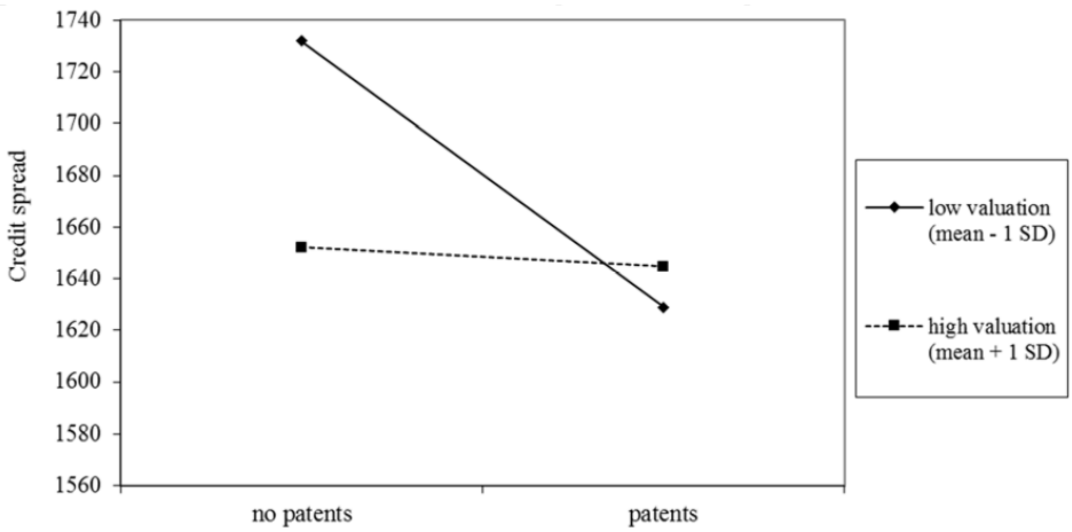

Fig.27: Relationship of patent (granted/pending) and credit spread (Cs) in VD and the interaction effect of firm's maturity on this relationship. Cs is the difference of 3-year swap rate (when VD issued) and the actual interest rate applied. For the sample, the Cs was on average 804.81 basis points and the valuation is a proxy of firm's maturity (Hesse, Lutz and Talmor, 2015).

Moreover, should be noticed that startups with more *re-deployable* patents had more access to VD (Hochberg, Serrano and Ziedonis, 2018). Regarding the *redeployability* of a patent, the recovery rating assessment for venture debt, could use as a guide, the bellow findings of Serrano and Ziedonis (2018) for failed VC-backed firms:

- The *trading conditions for the secondary patent market*. Specifically, periods of increased liquidity are related with higher lending activity.
- *Citations' number, patent's originality & patent's age (at startup's exit)*. More original patents, younger patents and those obtain more citations are more likely to be sold (also supported by Hochberg, Serrano and Ziedonis, 2018).
- *The patent citations as an indicator of firm-specific patents*. In particular, there should be a separation between patent citations that derived by subsequent inventions of a different firm and those derived by subsequent inventions of the focal startup (self-cites). As the findings indicated, a patent with more self-cites has a higher probability to be firm-specific and thus less redeployable.
- The *speed with which the patent are sold & the estimation of the tradeoff between benefits of patents' sale and costs for tracking buyer*. The costs include costs arising from negotiating, asset depreciation and hiring employees for the redeployment process. Findings indicated that in respect to medical devices, software and semiconductors industries for the US region, patents are sold quickly (mainly within a year after failure) and remain legally active.
- *The quality of VC that backed the startup*. Particularly, the findings support that patents of startups backed by high-quality VCs, have higher possibility to be sold after firms' failure. However, this finding could be affected by its interrelationship with factors such as the impact of VC on firm's capital constraints and on firm's overall performance.
- The *co-mobility of inventors & patents*. As argued, by de Rassenfosse and Fischer (2016), a potential problem in using intangible assets as collateral to secure venture loan is that in many cases the IP value is often bundled with the inventors. The study of the co-mobility of inventors & patents among different industries and regions could be an indicator for patent redeployability. Moreover, the findings indicated that the *probability* that inventors and their patents jointly move to the subsequent firm (patent buyer) is *higher* for patents with high share of *self-citations* and for patents that are *more original*.

The recovery rating methodology for startups should analyze the ability of the startup to develop *redeployable* patents to pledge as collaterals, based on firm's *industry* & *country* characteristics.

1.19. CRF & venture lending criteria: The case of SaaS startups

As it is indicated (Fig.28) as firms mature they have more options for debt financing. Specifically, leaving for pre-revenue stage, where startups can access the common senior-term loan, SaaS firms can also access the *Monthly Recurring Revenue (MRR) Line of Credit*. The latter debt instrument is based on firm's revenues and has a revolving structure. Generally, to access VD, minimum annual revenue of at least $200,000 to $1 million is required (Findventuredebt.com, 2018).

Profit / Loss	Equity Sponsor	Working capital financing	MRR line of credit	Senior term loan	Second lien term loan	Revenue-based financing	Mezzanine financing	Equipment loan / lease	Royalty-based financing
Pre-Revenue Companies									
Loss	No							✓	
Loss	Yes			✓				✓	
SaaS Companies									
Loss	Yes / No		✓	✓		✓		✓	
Profit	Yes / No		✓	✓		✓	✓	✓	
Life Science Companies									
Loss	No	✓						✓	✓
Loss	Yes	✓		✓				✓	✓
Profit	Yes / No	✓		✓	✓		✓	✓	✓
Other Industries									
Loss	No	✓				✓		✓	
Loss	Yes	✓		✓		✓		✓	
Profit	Yes / No	✓		✓	✓	✓	✓	✓	

Find Venture Debt LLC www.findventuredebt.com

Fig.28: Types of debt financing for startups & relevant startups characteristics (Findventuredebt.com, 2018)

Venture lenders prefer *recurring/predictable* revenue models and such models are presented in SaaS & subscription based startups. Since SaaS startups are one of the main VD issuers, CRF focuses on specific lending criteria that are compatible with the characteristics of SaaS industry.

In regards to *debt capacity* for revenue-stage SaaS startups, the common rule is: *Total debt obligations* = 3x to 6x *Monthly Recurring Revenue* (MRR).

Bellow, crucial metrics for SaaS startups are presented. The metrics are provided by the study of Kemell et al. (2019) and they are highly compatible with the venture lending criteria:

• *Customer churn*.

Venture lenders could focus on metrics such as monthly (lost customers/prior month total), annually and gross churn (total customer lost). Lenders for MRR line of credit usually ask for a maximum of 5%-15% annually churn rate (Findventuredebt.com, 2018).

• Metrics in respect to *user/customer engagement*.

• *Short-term* focused financial metrics such as *burn rates*, *MRR* and *month-on-month (MoM) growth*.

Specifically, lenders could analyze the way that the MRR is formed based on the new MRR (additional MRR from new customers), the expansion MRR/ upgrade (additional MRR from existing customers) and the churned MRR (MRR lost from cancellations or downgrades). In addition, lenders should focus on the *MoM MRR growth* given bellow:

MoM MRR Growth (%) = Net MRR (This Month) - Net MRR (Last Month) / Net MRR (Last Month)

Generally, 15-20% MoM MRR growth is a sufficient target for post-Seed/pre-Series A SaaS startups (Tomasz Tunguz, 2014).

• *Customer/User-focused* financial metrics

Specifically, for early stage startups, the *Customer Acquisition Cost* is a useful metric.

Beside the above metrics, Venture Lenders are looking for *strong gross margins*. Moving from the early stage, SaaS firms are able to achieve gross margins of 70-80%, due to economies of scale (David Cummings on Startups, 2014). On the other hand Tomasz Tunguz (2014) provided the gross margins trends for public firms based on their life stage, which could be a guide for startups (Fig.29) (Tomasz Tunguz, 2014).

Estimating future MRR and gross margins for early stage firms is challenging. Lenders should examine if the firm has achieved strong MRR growth for subsequent months. Referring to growth projections, accurate estimation is crucial.

Another metric that refers to the *revenue growth* of SaaS firms and is used by VCs but also could be useful for the VLs' analysis is the SaaS_Quick Ratio given by VC Mamoon Hamid:

SaaS_Quick Ratio = (New MRR + Expansion MRR) / (Contraction MRR + Churned MRR)

With Contraction MRR, equals to Lost MRR from existing customers.

Generally, VCs are looking for high ratios with the optimal number being around 4. The ratio is not applied for startups in their first year of operations, while for early stage firms achieving high new MRR numbers and low churn it's easier. Setting from early on high expansion MRR numbers as future milestones could be an incentive for startups to achieve efficient growth and customer success (Whalley, 2015).

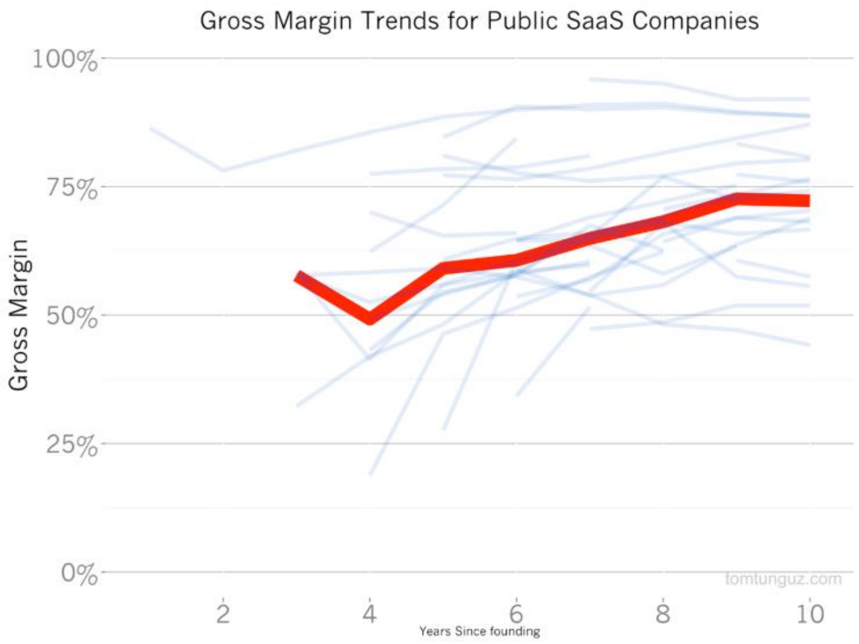

Fig.29: Gross Margins trends for Public SaaS Firms (Tomasz Tunguz, 2014)

As it was mentioned, the payment of VD is based on the subsequent financing round, so for early stage SaaS firms the *size & growth*, *financial* and *SaaS value driver* metrics presented on Fig.30 and Fig.31 could be utilized by the VLs.

	Angel / Seed	Series A	Series B
SIZE AND GROWTH			
Employees	10	38	67
YoY Growth Rate	100%	80%	126%
ARR	$0.5M	$3.8M	$7.5M
FINANCIAL			
Sales & Marketing Spend	35%	45%	50%
R&D Spend	60%	40%	40%
Subscription Revenue	95%	91%	91%
Monthly Burn Rate ($ in 000s)	$39	$150	$317
SAAS VALUE DRIVERS			
CAC Payback (months)	6 months	12 months	14 months
Sales Efficiency	1.19	0.98	0.83
Logo Retention	90%	90%	86%
Net Dollar Retention	100%	100%	105%

Fig.30: Metrics of early stage SaaS firms by financing round for a sample of 420 firms. With ARR equals to the annual recurring revenue (FANNING and POYAR, 2018)

YoY Growth Rate	Change in annual recurring revenue at the end of 2017 vs. 2016.
FINANCIAL	
Sales & Marketing Spend	Spending on Sales & Marketing, including headcount, as a % of year-end 2017 ARR.
R&D Spend	Spending on R&D, including headcount, as a % of year-end 2017 ARR.
Software Revenue	Revenue derived from subscriptions as a percent of total 2017 revenue.
Monthly Burn Rate (in 000's)	Net monthly burn rate basis at the end of 2017 (total $ lost each month, negative values = profit).
SAAS VALUE DRIVERS	
CAC Payback (months)	Months of subscription gross margin to recover the fully loaded cost of acquiring a customer.
Sales Efficiency	Incremental revenue contribution returned by Sales & Marketing spend.
Logo Retention	Annual logo retention seen in cohorts.
Net Dollar Retention	Annual net dollar retention (after upsells & expansion) seen in cohorts.

Fig.31: Definition of the SaaS metrics (FANNING and POYAR, 2018)

The venture lending criteria could utilize the bellow indicators (Glen Mello, 2015):

- The available startup's cash.
- The burn rates.
- The cost to hit certain milestones/analysis of inflection points. Specifically, go-to-market milestones are highly significant. Usually, for early-stage technology hardware firms the gross margins are quite weak compared to software firms, making cost of manufacturing and cost of shipping highly significant factors for raising capital.
- The venture's team. VLs are seeking for quality and specifically if the team has repeat entrepreneurs and sufficient track record.
- The existence of a prior relationship among VLs and the venture's team.
- The existence of a prior relationship among VLs and VCs.
- The Market opportunity.
- The startup's business model and the product.
- The VCs' syndication.
- Industry benchmarks and company statistics on global basis.
- The milestones that the firm should hit to move on to the next equity round.

Referring to *firm's cash*, as it is already indicated, startups should raise VD directly after VC investment, when there is a *lot of cash available* (de Rassenfosse and Fischer, 2016). Given that, when the firm has low amount of cash shouldn't issue VD as bridge financing option. Generally, startups should utilize VD when they have a momentum. However, in case of issuing VD as a substitute of an inside bridge (equity round) modeling future cash flows is highly important. Specifically, the firms should estimate if the debt capital is sufficient to help them make it to the next round (Columbia Lake Partners | Financing European Growth, n.d.).

VLs are seeking for *low burn rates* given that the issuance of VD increases the firms' burn. However, the factors of *firm's life-stage*, firm's *industry characteristics* and the *impact of burn rates on firm's survival* (further indicated on the present thesis) should be considered. In case where a startup raises equity round earlier than the statistics suggest (firms characteristics, industry, country, etc.), may have high burn rates. However, startups that manage to access capital early-on could be a signal of their quality and a signal for their future performance. In the same direction, the phenomenon that *capital intensive* firms such as biotech startups obtain equity financing could reflect the *VC certification*.

1.20. CRF & venture lending criteria: The case of life science startups

Life science startups are capital intensive firms and their valuation differs from startups of other industries. Similarly, VLs set specific criteria for lending. The *probability of success* and the *VC funding* by phase of drug's development (Fig.32, Fig.33), indicate the characteristics of biotech sector.

Generally, VD is raised by firms who had received *FDA approval/CE Mark* or are in the pivotal trial stages (for Medtech, Fig.34). However, early-stage technologies (Phase I/II or preclinical) also access venture lending. Bellow crucial criteria that VLs are focused on for life science startups, are presented (Markunas, 2016):

- Analysis of Key clinical/developmental/strategic milestones.
- Analysis of inflection points.
- Assessment of IP.

- Current cash runway. Specifically, VLs are looking for a 6 to 12 months of cash runway on the balance sheet at all times.
- Clinical results to date (regulatory positioning & timing).
- Broad product pipeline. Moreover, VLs are seeking for firms that can effectively manage their product pipeline.

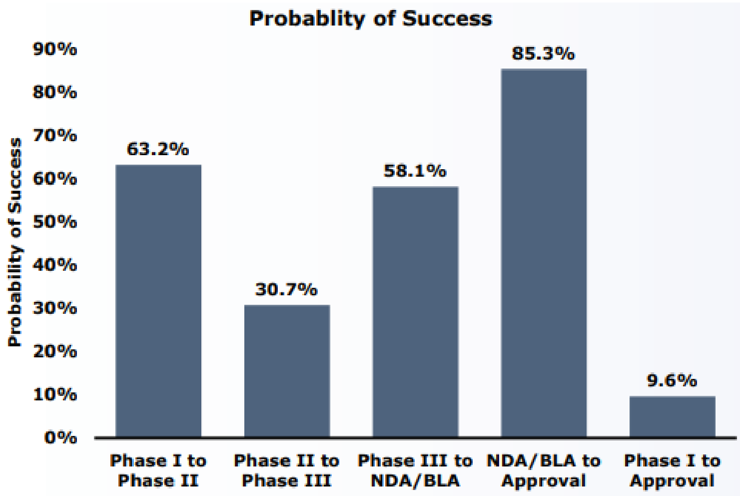

Fig.32: Probability of success by phase of development for biotechnology firms for the period 2006-2015 (BIO Industry Analysis Report, 2016)

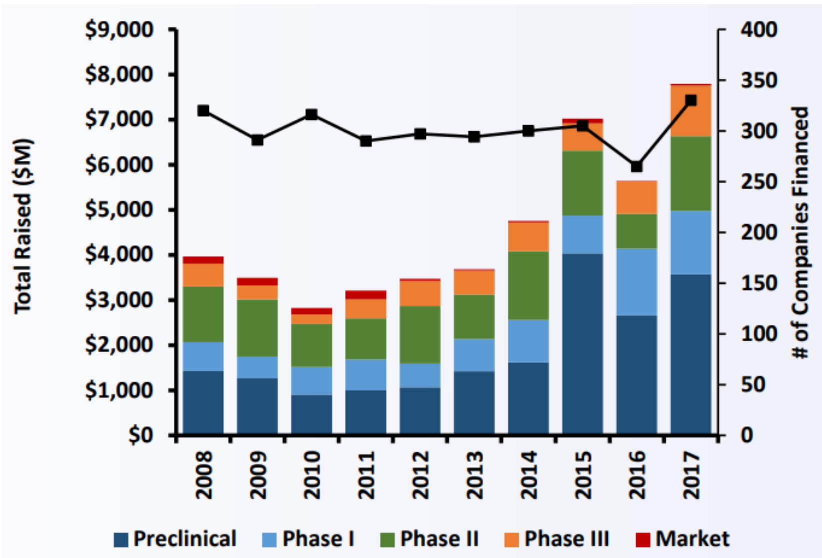

Fig.33: Venture funding by phase of development, for 2008-2017 in the US context (Thomas, 2018)

Moreover, the CRF could utilize the bellow findings that indicate the usage of the debt (Beam, 2014):

- Given that *medical device* firms of class III (Fig.34) often pursue CE Mark prior to FDA approval, it is optimal for them to use VD when they have obtained *CE Mark* and they are initiating the *IDE trial* (an IDE permits the device to be used in a clinical study in order to collect safety and effectiveness data). At this stage the technological risk is lower and the VD could be repaid by forthcoming *exit* or *strategic partnership*.
- *Single-asset firms* (medical device or biotech/pharma) shouldn't raise VD to achieve milestones referring to the completion of clinical trials with binary results (success/ non-success). Firms should use VD between positive results (achieved milestones) and next financing event. However, if the clinical trial is open label (all parties of trial are aware of participant's treatment) or there are strong indicators that the primary endpoint will be achieved, VD can be utilized earlier.

Pharmaceuticals			Medical Devices		
Phase	Subjects	Purpose	Stage	Subjects	Purpose
0 Pilot / Exploratory	10 - 15	• Test a very small (subtherapeutic) dose of a new drug to study its effects & how it works in the human body. • Not all drugs will undergo this phase.	Pilot / Early Feasibility / First-in-Human	10 - 30	• Small study to collect preliminary safety & device performance data in humans. • Guides device modifications &/or future study design.
I Safety & Toxicity	10 - 100	• True first-in-human study to test safety & toxicity, usually in healthy humans.	Traditional Feasibility	20 - 30	• Assess safety & efficacy of the near-final or final device design in patients. • Guides the design of the pivotal study.
II Safety & Efficacy	100's	• Assess efficacy & safety in patients.			
III Clinical Effectiveness	100's – 1000's	• Confirm clinical efficacy, safety & adverse events. • Compare the new drug to standard care or a commonly used drug.	Pivotal	100's	• Large study to confirm clinical efficacy, safety & risks. • Statistically driven.
IV Post-Market / Surveillance	1000's	• Monitor long term effectiveness & safety in the general population.	Post-Market	1000's	• Monitor long term effectiveness, safety & usage in the general population.

Class	Risk	Clinical Trials?
I	Minimal	No
IIa	Low to moderate	Maybe
IIb	Moderate to high	Maybe
III	High	Yes
AIMD	High (Active Implantable Medical Devices)	Yes

Fig.34: Comparison of pharmaceutical trial phases-medical device trial stages (left) and Classification of medical devices (right) (Genesis Research Services, 2018)

Regarding *biotech* firms, VLs should focus on their characteristics. Specifically, such firms achieve exits *earlier* in respect to *commercial development* (Fig.35, Fig.36). In some cases biotech firms achieved IPOs before the completion of the clinical trials and the IPO should be seen as a funding event and not a final validation of firm's commercial prospects (Lebret, 2018).

Based on biotech's IPO characteristics, lenders should consider the VD repayment process through an exit and the *upside potential* (warrants) based on firm's post-IPO performance. Additionally, in such capital intensive firms the *cost efficiency* is a highly important factor.

Field	#	#VC-backed	% VC	VC ($M)	Time to exit	# M&As	% M&A	M&A ($M)	# IPOs	% IPO	Value at IPO ($M)	12m. after IPO
Biotechnology	258	171	66%	44	6.6	66	26%	77	82	32%	203	176
Medtech	211	146	69%	37	7.8	76	36%	144	48	23%	237	185
IT Hardware	879	485	55%	49	7.9	378	43%	219	154	18%	635	443
IT Software	803	380	47%	34	6.6	336	42%	137	78	10%	577	661
Internet	745	395	53%	42	4.0	269	36%	159	66	9%	1'977	2'477
Other tech.	192	27	14%	110	11.0	39	20%	124	12	6%	297	521

Fig.35: Startups' features by industry. Sample of 5,600 Stanford-affiliated corporations (Lebret, 2018)

Field	#	Sales ($M)	Income ($M)	FTEs
Biotech.	122	10	-17	76
Medtech	22	21	-12	173
HW/Comp./Tel	68	92	-7	432
Semiconductor	36	63	-5	386
Software	62	110	1	582
Internet	106	336	3	1344
Energy/Env.	17	58	-48	500
Other	6	169	-15	391

Fig.36: Sales Incomes & Employees at time of IPO. Sample of 400 filed firms Stanford-affiliated corporations (Lebret, 2018)

Chapter 2- The basic CRF model

The proposed CRF model consolidates the various models described in the existing literature and allows the inclusion of additional models (like industry specific – SaaS, Life science, etc.) without losing generality and consistency.

The present thesis includes in the basic CRF the following models:

M1: Gonçalves, Martins and Brandão (2014).

M2: Sohn and Kim (2012)

M3: Pederzoli, Thoma and Torricelli (2012)

M4: Angilella and Mazzù (2015)

M5: Proksch et al. (2016)

M6: Berman and Hernandez (2017)

The basic CRF model normalizes each method estimator on a relative scale of 5, benchmarked against mature firms rated by S&P (or other agencies) and provides an aggregated holistic picture using a graphic multidimensional representation. The Issue receives a score between 0 and 5 on each of the models and the overall rating is presented in a consolidated radar graph (Fig.37).

The basic CRF follows the concept of PME method used by VCs to access the performance of the fund against a public benchmark. Each one of the models included in the CRF, addresses different indicators that are related with firm's failure risks, covering the various aspects of startups' credit risk. By setting as a benchmark the performance of strategically selected rated firms in the proposed indicators "bridges" the credit risks of VD with the S&P rating. The value of CRF lies on the significant conclusions that could be extracted by the comparison of the assessed firms with the selected rated firms. CRF leverages the ratings of the firms/benchmarks in order to evaluate the credit risk of firms that want to issue VD.

The user could utilize the CRF model by comparing a population of startups to firms which have established credit ratings but also have similar characteristics to the population (industry, region etc.) (Fig.38). For example, referring to M1 model, evaluating the performance of a biotech early stage firm (headquartered in an EU country) based on indicators related with failure risk in the first 3 years of operations, against the relevant performance of the rated biotech firm (same country) for its first 3 years of operation, could provide valuable insights for firm's credit risk assessment. Moreover the model could be used for group comparison, for example the performance of biotech firms in one country compared to these of other countries.

Furthermore, additional models could be included in the basic CRF model. The factors that are addressed on the proposed framework could help towards the inclusion of more models in the basic model.

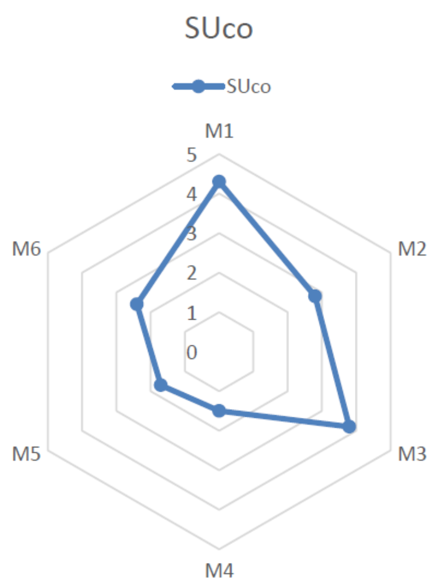

Fig.37: Example of an overall rating for the basic CRF model

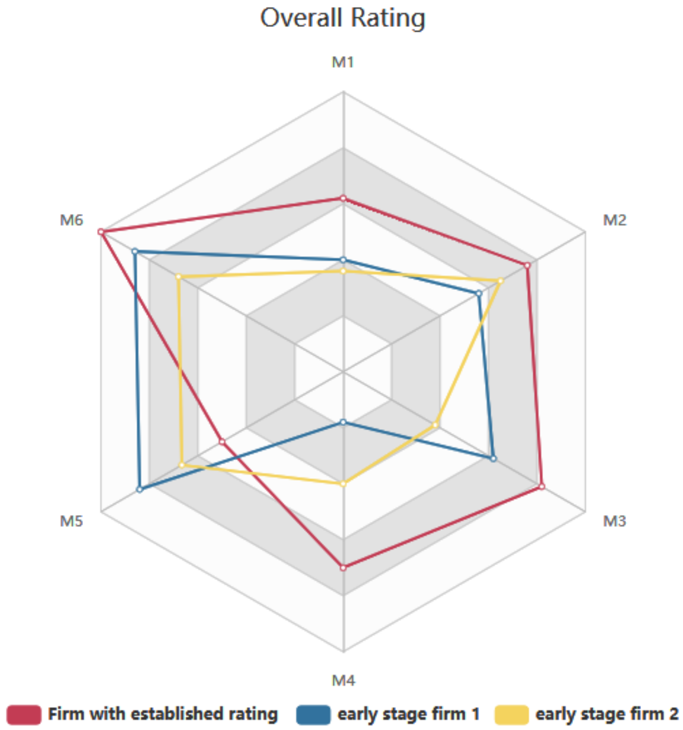

Fig.38: Overall ratings of two similar early stage firms, graph also includes the performance of the firm used as benchmark

Chapter 3- Conclusions

The present thesis proposes a CRF model for early stage firms, extracted by the general CRF that is extensively defined. The basic CRF includes and consolidates 6 models provided by the literature although additional models can be included without loss of generality and consistency. Specifically, the basic model normalizes each method estimator on a relative scale of 5, benchmarked against firms with established credit ratings and provides an overall rating represented on an aggregated radar graph. The significance of the basic model derives from the fact that it utilizes the credit rating scales of well-known agencies for the assessment of startups' credit risk. This way, information asymmetry between lenders and early stage firms could be reduced. Generally, the CRF model follows the concept of PME method used for VCs' performance analysis.

The CRF also include supplementary indicators to the proposed basic CRF model. The CRF utilizes the concept of notching of S&P rating, distinguishing between issue and issuer rating. Based on this concept, the CRF focuses on the significance of firm's recovery potential. The recovery rating is influenced by the loan structure. Given, the high levels of prepayment risk, CRF accesses the existence of prepayment/origination fees or end-of-term payments. Similar to the inverted-U relationship of R&D intensity-S&P credit ratings, the inverted-U relationship of R&D intensity-startups' survival is proposed by the relevant literature. In respect to this perspective, the basic CRF includes the analytical model M6, setting the normalized burn rate as an estimator of startups' failure probability. CRF also focuses on the VCs' quality that invested on the firm. Specifically, the invested VC's funds performance and their impact on firms' performance, the syndication frictions and the risks of VC-backed firms are considered. Towards this direction the basic CRF includes the M5 model addressing the firms' failure risk in respect to VC quality. Given the significance of follow on financing for loan repayment, the proposed framework focuses on the aspects of VC quality related to VC's commitment and VC's track record. Furthermore, the cyclical component of VC markets, the VC valuations and the IPO /M&A activity are considered. The CRF denotes the significance of IP for both firms' overall creditworthiness and their recovery assessment. Specifically it focuses on startups' patents and trademarks. For the use of patents as collateral CRF targets on patents redeployability. Additionally, the CRF includes industry-specific lending criteria for SaaS and life science firms. The supplementary indicators provided in the CRF could be leveraged for the inclusion of relevant models in the basic CRF.

In conclusion, the proposed CRF could be utilized by early stage firms or venture lenders. The CRF could be a useful tool for the access of early stage firms to financial resources, using debt as borrowing instrument.

For future research the bellow topics are proposed:

- The validation of the basic CRF model using data from specific firms.
- The inclusion of additional models in the basic CRF. Specifically, the inclusion of models relevant with the venture lending criteria and the characteristics of high tech startups.

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