UNIVERSIDADE FEDERAL DE PERNAMBUCO
CENTRO DE CIÊNCIAS SOCIAIS APLICADAS
DEPARTAMENTO DE CIÊNCIAS CONTÁBEIS E ATUARIAIS
PROGRAMA DE PÓS-GRADUAÇÃO EM CIÊNCIAS CONTÁBEIS
DOUTORADO EM CIÊNCIAS CONTÁBEIS

VANESSA JANISZEWSKI

DATA DRIVEN WORTH FUNDING CONDITIONS: A STUDY ON THE LIKELIHOOD OF VENTURE CAPITAL BACKED COMPANIES' SUCCESS IN BRAZIL

Recife

2022

VANESSA JANISZEWSKI

DATA DRIVEN WORTH FUNDING CONDITIONS: A STUDY ON THE LIKELIHOOD OF VENTURE CAPITAL BACKED COMPANIES' SUCCESS IN BRAZIL

Tese apresentada ao Programa de Pós-Graduação em Ciências Contábeis do Departamento de Ciências Contábeis e Atuariais da Universidade Federal de Pernambuco, como requisito parcial para obtenção do título de doutor em Ciências Contábeis. Área de Concentração: Informação Contábil.

Orientador: Profa. KatherineElizabeth Horton, Ph.D.

Recife

2022

Catalogação na Fonte
Bibliotecária Ângela de Fátima Correia Simões, CRB4-773

J33d Janiszewski, Vanessa
Data driven worth funding conditions: a study on the likelihood of venture capital backed companies' success in Brazil / Vanessa Janiszewski. – 2022.
160 folhas: il. 30 cm.

Orientadora: Profª. Katherine Elizabeth Horton, Ph.D.
Tese (Doutorado em Ciências Contábeis) – Universidade Federal de Pernambuco, CCSA, 2022.
Inclui referências e apêndices.

1. Capital de risco. 2. Empresas. 3. Competência administrativa. I. Horton, Katherine Elizabeth (Orientadora). II. Título.

657 CDD (22. ed.) UFPE (CSA 2022 – 034)

VANESSA JANISZEWSKI

A DATA DRIVEN WORTH FUNDING CONDITIONS: A STUDY ON THE LIKELIHOOD OF VENTURE CAPITAL BACKED COMPANIES' SUCCESS IN BRAZIL

Tese apresentada ao Programa de Pós Graduação em Ciências Contábeis da Universidade Federal de Pernambuco, Centro Acadêmico CCSA, como requisito para a obtenção do título de Doutora em Ciências Contábeis. Área de concentração: Informação Contábil.

Aprovado em: 25/04/2022.

BANCA EXAMINADORA

Participação via videoconferência

____

Prof.ª Katherine Elizabeth Horton, PhD (Orientadora)
Universidade Federal de Pernambuco

Participação via videoconferência

____

Prof.ª Dr.ª Anabela Alves Carvalho (Examinadora Externa)
Uminho - PT

Participação via videoconferência

____

Prof. Dr. Aldo Leonardo Cunha Callado (Examinador Externo)
Universidade Federal da Paraíba

Participação via videoconferência

____

Prof. Dr. Giuseppe Trevisan Cruz (Examinador Externo)
Universidade Federal de Pernambuco

Participação via videoconferência

____

Prof. Luiz Carlos Miranda, PhD (Examinador Externo)
Universidade Federal de Pernambuco

Dedico este trabalho ao meu irmãozinho, Daniel Janiszewski, que sempre acreditou em mim e que hoje descansa em um lugar melhor.

AGRADECIMENTOS

Em primeiro lugar desejo agradecer à minha orientadora KatherineHorton, por toda contribuição, apoio e inúmeras reuniões. Sem você eu não teria conseguido. Desejo agradecer também ao meu eterno orientador e amigo Prof. Aldemar Araújo Santos, com certeza esta tese é um fruto de seu trabalho.

Gostaria de agradecer ao Departamento de Ciências Contábeis, aos Professores da Banca de avaliação, à CAPES pelo financiamento e confiança, aos professores do departamento pelo conhecimento, aos meus colegas de turma e à minha família.

Por fim, gostaria de agradecer ao meu esposo, Domingos Sávio Pereira Salazar, que me apoiou em todas as etapas para eu conseguir chegar até aqui.

RESUMO

O presente trabalho busca aprimorar a compreensão a respeito de empresas financiadas por capital de risco e métodos de se alcançar sua mensuração quanto a diferentes critérios de sucesso. Para tanto, esta tese é dividida em quatro capítulos: (i) estudo bibliográfico a respeito de empresas financiadas por capital de risco, sua origem, fundamentação teórica e desenvolvimento; (ii) revisão sistemática de estudos empíricos que levantam 'successo' como métrica de mensuração das empresas financiadas por capital de risco e como tais definições se relacionam com diferentes variáveis preditivas; (iii) estudo empírico com dados de empresas de empresas brasileiras financiadas por capital de risco, o qual faz uso de variáveis independentes não financeiras e cinco definições de sucesso, a fim de propor diferentes modelos de regressão estatística não lineares, e; (iv) discussão geral ressaltando os principais achados, limitações e pesquisas futuras. A presente pesquisa levantou que existem cinco grupos comumente utilizados pela academia quanto à definição de sucesso, são eles: saídas (exits), sobrevivência, montante de capital de investimento levantado, número de rodadas de investimento e escalas autodesenvolvidas. Diferentes definições de sucesso podem sim levar a diferentes resultados. Em nossa pesquisa empírica com dados brasileiros, como principal resultado, foi encontrado que montante de capital de investimento levantado é a variável dependente que possui um maior poder associativo com as variáveis não financeiras levantadas, apresentando um KS máximo de 37% e AuRoc de 0,82. As variáveis independentes que mais se destacam foram quanto à educação estrangeira dos fundadores, portador de diploma MBA e quantidade de fundadores sócios.

Palavras-chave: Capital de Risco, Empresas financiadas por capital de risco, Fatores de Sucesso.

ABSTRACT

The present work seeks to improve the understanding of Venture Capital (VC) backed companies and methods of achieving their measurement in terms of different success criteria. In order to do so, this thesis is divided into four chapters: (i) a bibliographic account of VC backed companies, their origins, theoretical foundations and development; (ii) a systematic review of empirical studies that cite 'success' as a measurement metric for VC backed companies and an analysis of how different variables predict different definitions of success; (iii) an empirical study with data from Brazilian VC backed companies, which examines the relationships between non-financial independent variables and five definitions of success, in order to propose different non-linear statistical regression models, and; (iv) general discussion highlighting the main contributions, limitations and future research. The present research found that there are five measures commonly used by academia to define success. These are: exits, survivability, funding amount raised, number of investment rounds, and self-developed scales. Different definitions of success can lead to different results. In other words, non-financial predictors are differentially related to different success outcomes. In our empirical research with Brazilian data, as main results, we found that the funding amount raised is the dependent variable that has the highest associative power with the chosen non-financial variables, presenting a maximum KS of 37% and AuRoc of 0.82. The independent variables that stand out the most were the founders' foreign education, if they are MBA degree holders, and the number of founding partners.

Keywords: Venture Capital, Venture Capital Backed Companies, Success Factors.

List of Figures

List of Tables

Summary

CHAPTER 1 - LANDSCAPE OF VENTURE CAPITAL MARKET

1. Introduction

Venture Capital (VC) is a type of private equity that funds and invests in small and early-stage firms with a high risk and high return profile. It is usually regarded as a short life investment (five to ten years), with the main objective of the VC investor being to enter a company with high potential future worth, while it's still in its embryonic stage, insert the capital needed to grow in a given period of time, guide the company into developing all this potential, and sell it – which is called an exit.

The role of Venture Capitalists in the United States after World War II cannot be neglected. The rise of high-risk investments in small companies enabled disruptive technologies that shaped the current information economy and fueled the idea of limited partner ventures investing (Zider, 1998; Gompers & Lerner, 2000; Lerner, 2022). Such investments are characterized by uncertainty, information asymmetry and asset intangibility (Kaplan & Lerner, 2016; Ewens, Gorbenko, & Korteweg, 2022). Following the relative success in the USA and the sometimes-overrated tales from Silicon Valley, the Venture Capital modus operandi reached emerging economies, such as the Brazilian market, with its own limitations (De Lima Ribeiro & de Carvalho, 2008; Leonel, 2019).

What determines a successful VC investment, in term of profitability, is the amount of money created and gained in the moment of their exits. The exit may be due to the invested company going public (IPO or initial public offering) or selling it to a private investor – the acquirer may be another VC backed company.

Thus, this market is characterized by VC companies, who are those who invest, and the VC backed companies, who are the early stage high-risk and high potential growth firms that receive this private funding.

Another common occurrence that happens in this type of investment market, as it does in all high-risk assets, is the high diversification of investors' capital.

While the media, journals, articles, as well as society's perception are marked by overwhelming cases, such as highly successful and profitable ex-startups or some dead-end high loss disappointments, the majority of funded ideas (firms) rise and die within a short life span.

In this sense, recent prior research has started to explore some of the possible characteristics that determine the success or failure of venture investments, as is detailed in the following topics.

The purpose of this thesis is to explore Venture Capital's academic landscape, in terms of the common-ground concepts researchers have developed and established concerning how to assess the value of VC backed companies, as well as to identify the areas where there is still work needed to find a common ground of concepts. That is, this thesis aims to understand a) how academia has assessed VC backed companies' success, b) the many definitions of VC's success used in the literature c) how different definitions may/can lead to different results d) the use of non-financial information in the attempt to build a valuation model type for the VC market, e) the extent to which this non-financial data can predict private held equity venture companies' outcomes. Last, this thesis also aims to empirically analyze how nonfinancial data relates to the success of companies in the Brazilian VC market.

The present research is divided into four chapters. The first and current one provides an overview of the VC market and research landscape. Chapter two and three are two different, but complementary, studies. Chapter two is Study One, where a systematic review is carried out focusing on VC backed companies' definitions of success. Chapter three is Study Two, in which an empirical data driven set of models is developed with VC Brazilian data, where we aim to empirically examine what was discussed in the two previous chapters. Finally, in Chapter Four the results are laid out, as well as the research contributions, implications, limitations, and suggestions for further research.

1.1. Research Purpose and Value

Growth-oriented ventures are essential to society's development, and Venture Capital is a significant method for promoting their evolution. Landström (2007, p.3) states that "the importance of venture capital makes it essential for academics to understand the way the venture capital market operates".

New information and greater knowledge on the VC market, how it operates, and how we can assess its potential, are both relevant for investors' rational decision-making processes as well as for companies who aim for some capital funding.

It is relevant for VC companies in the sense that they need to know the shape of the high potential companies, those who have more chance of growing and becoming the next *unicorn* (i.e., a privately held company with U$ 1 billion+ of valuation). The VC companies need to have access to some sort of value type model to make reasonable investment decisions.

This matter is also relevant for the sake of the companies that aim to prosper with the help of external capital. In order to approach venture capitalists for funding, these entrepreneurs must first have an action plan to self-assess their value and their funding chances. It may be extremely vital, for instance, to first consider what characteristics their ideal investors are seeking, as well as pursuing what they might lack in order to thrive.

According to Hisrich and Jankowicz (1990) and Mitchell, Friga, and Mitchell (2005), venture capitalists use many subjective criteria and intuition in their decision-making. They argue that in view of this, research must focus on developing methods that model the intuition and the subjectiveness in the decision-making process involved in their investment selection.

Gathering more information and having a better knowledge of the decision-making process within this type of market is relevant for the economy's efficiency, and in this sense, it is an academic duty to pursue and examine such a theme.

Furthermore, the research has an implicit ambition to explore beyond financial statements' boundaries, an objective which has already been observed as important in classic accounting research, as we'll explain in the following text.

One of accounting's aims is to provide relevant information to investors and improve the quality of their decision-making. This goal is mainly delivered by examining the financial statements provided periodically and financial analysis procedures. Nevertheless, one relevant question to think about is if accounting-related financial information is sufficient to understand all the decision-making processes that determine a company's market value. But this question isn't a novel one. Ball and Brown (1968) studied the relationship between revision in stock price and change in accounting earnings. Their findings were so relevant that in 2019 they had a second version of the paper republished repeating their conclusions. By using revision in price as a measure of the flow of value-relevant information about a firm, the research design allowed them to estimate two fundamental properties of accounting earnings: "Do accounting earnings incorporate information that investors consider value relevant? (Yes). Do accounting earnings incorporate value-relevant information in a timely fashion? (No)" (Ball & Brown, 2019, p. 410).

Although we are here concerned with private VC backed companies rather than publicly traded ones, there is a fundamental common area of interest and that is to understand a firm's valuation beyond the limits of financial information.

The present research has as its main goal to address the following question:

Question I: Can the success of a Venture Capital Backed Company be predicted (at its founding) by non-financial information? And if so, how is it shaped by the following four indicators (1) External factors, (2) Investor factors, (3) Characteristics of the product / service, financial, business model and proposal, and (4) Characteristics of the entrepreneur and/or the management team.

In chapter three we conduct an empirical study using Brazilian data that focuses on the characteristics of the entrepreneur and/or the management team and their association with VC backed companies' success. These non-financial data on founders/entrepreneurs include their education, expertise, experience, gender, country of origin and so on.

In order to conduct the empirical analysis, we first confront a great issue concerning what is understood as ‘success’ in the Venture Capital market.

As stated by Milosevic (2018), it would be ideal to measure performance by the returns of VC firms. However, VC firms are quite reluctant to disclose their returns publicly. For this matter, a great deal of academic research has considered ‘success’ of investments as a way to separate the good and the bad investments and proceed with their research.

Many studies have analyzed the success of VC investments, including Gompers and Lerner (2000), Hochberg, Ljungqvist and Lu (2007), Sorensen (2007, 2008), Nahata (2008), Gompers et al, (2008), Zarutskie (2007), Brander, Amit, and Antweiler (2002), Cumming and MacIntosh (2003), Nahata, Hazarika, and Tandon (2014), Humphery-Jenner, and Suchard (2013), Milosevic (2018) and Nanda, Samila and Sorenson (2020).

This research overcomes the lack of financial information by examining a company’s ‘success’, but they do so in many different ways. There is a lack of common language and well-defined definitions in VC research. This issue is addressed extensively in chapter two and brings us to this research’s next key question:

Question II: *How* do academics define and operationalize the success of Venture Capital backed companies? And how do the predictors of success found in academic studies vary depending on the different definitions of success adopted by these studies.

2. Literature Review

2.1. Origins of Venture Capital

Venture capital can be seen as an ancient phenomenon and activity. Landström (2007) traces it back as far as the Babylonian era. One could argue, for instance, that the decision made by the King of Portugal to finance the expedition of Pedro Álvares Cabral, which can be considered as high risk and highly profitable, can be seen as a Venture Capital investment for Portugal.

Most researchers agree that it is not possible to pin an exact date on when the first Venture Capital investments took place. Rather than trying to find a specific moment, they argue that this kind of investment is to be looked at as a rising need that has been developing continuously in different periods of time (Gompers,1994; Rind, 1981).

If you take a look at the USA's history, for instance, in the late nineteenth century, domestic and foreign groups were resources of capital used to develop several new industries such as railroads, steel, petroleum and glass. These investments can be seen as seeds to VC investments but still in a very primitive way.

It was later, after World War II that modern Venture Capital had formally begun. The two decades that followed the war were characterized by wealthy family groups who became active venture capitalists, fomenting the rise of not only profitable companies, but nonprofits ones like universities as well.

The mid 1960s was a big moment for VC, as it is generally known as the first wave of CVC (Corporate Venture Capital). These are formal corporations that invest mainly in Venture Capital, focusing on investments with an above-average financial return, as we will see in the next section. According to Crunch Base data, as well as Global Corporate Venturing (GCV), today we have over 750 CVCs worldwide, while we have over one hundred thousand other types of investors.

Although an important mark for venture capital, it didn't last long. VCs all ended abruptly in the seventies when there was a decline in the public market for new issues. In the years between 1974 and 1975 the total capital raised by Venture Capital collapsed and vanished into almost nothing. This was due to the collapse of IPO (Initial Public Offerings) as well as the primary market, which made the VC investments impossible to maintain. It was the end of Venture Capital, some stated, even suggesting that a "recovery of interest is unlikely" (Meade, 1977, p. 663).

Rather, in a couple of years, things changed abruptly and these cycles of ‘crashes’ occurred more than once, always in some way associated with the stock market performance.

In the 1980s, the VC landscape intensified. Information technology rose and opened a new model of high-growing companies. These events revitalized public markets and created the need and exact fit for Venture Capital investments.

Apart from the upswing of technology, there were some additional factors that also contributed to this revitalization, like tax reductions and changes in SEC (Securities and Exchange Commission) regulation:

> These factors have led to substantial portfolio returns for most venture capital partnerships over the last five years (generally ranging from 2 & 40 per cent compounded annually) as against a flat stock market (Rind, 1981, p. 171).

Those who announced the death of VC investments were proven wrong. While in 1975 there were only four investors and they only raised an amount of sixteen million dollars, in the year of 1979 more than a billion dollars in investment was raised. Two years later that value tripled, with over four hundred groups of investors (Rind, 1981).

Today the amount of capital invested by VCs has skyrocketed - over nine hundred thousand billion dollars are currently invested. This phenomenon has spread throughout the world, including in developing countries such as Brazil, although US and European companies still represent a significant part of these investments.

Venture Capital funding today focuses on finding early-stage high risk/high return firms that include different types of companies, such as biotech, artificial intelligence, machine learning, financial (for example fintechs, insurtechs, etc.), internet, software and others, all with the potential of rapid growth in common (not to say that technology always constitutes the largest part of the rapid growth potential phenomenon).

Recent Venture Capital investments are applying a “spray and pray” technique, where the available capital is spread over many startups with lean hypothesis testing, such as social networks. Consequently, this reduces the overall investments in costly ideas with a long-term payoff, for instance, biotech and clean energy (Ewens, Nanda, & Rhodes-Kropf, 2018). This landscape was shaped by technology shocks, such as the introduction and popularization of cheap cloud computing such as the Amazon Web Services (AWS) post 2006, which allowed tech-enabled companies to scale quickly without requiring an initial large infrastructure investment.

Although innovative business models are hard to understand under traditional valuation frameworks, accounting information still plays an important role in VC-backed investments. Barth, Beaver and Landsman (2001) showed that accounting information is as relevant as non-financial information in the valuation of German startups with accuracy comparable to that of publicly traded companies. In terms of non-financial information, the authors identify five main factors based on previous literature: team composition, founding team size, management team size, CEO education and expertise and team experience.

Traditional valuation models such as the Discounted Cash Flow (DCF) might incorporate uncertainty in the input variables which ultimately results in uncertainty in the valuation prices (French & Gabrielli, 2005; Korteweg & Nagel, 2016). However, technology shock is unpredictable and might change an entire industry or sector, which highlights the need for valuation models to adapt quickly and be data driven.

Additionally, the Venture Capital market deals with the additional uncertainty created from the impossibility of a startup to provide statistically reliable accounting information. In this case, it is not possible to apply standard valuation techniques usually designed for publicly available companies with full information disclosure. Therefore, the development and formalization of auxiliary valuation data-driven models might partially explain the VC decision-making process (Miloud, Aspelund & Cabrol, 2012) as well as startups' success in funding rounds.

The effect of VC seems to go beyond capital and governance. It was recently found that VC-backed companies manage tone in IPO, i.e., they show less optimism in security registration filings (Thng, 2019). This is measured in terms of positive versus negative words in textual cues from the disclosure of regulatory information using previously known methods (Clements & Reade, 2016). In this case, tone management is even more evident when VCs hire Big 4 auditors and invest in tech firms, among other traits. Sometimes VC influence is documented to surpass the IPO stage as some VCs remain as executives and retain equity for some years after the IPO (Celikyurt, Sevilir & Shivdasani, 2014). As further evidence of the impact of VC-backed companies in valuation models, some studies suggest that VC-backed firms are mispriced and susceptible to large surprise unexpected earnings (SUE) per share compared to firms without VC financing. This finding was linked for instance with higher litigation risks (Lowry & Shu, 2002).

Another source of impact on IPO performance is the intrinsic features of the VC companies (age, type, country) such as the size and diversity of the VC syndicates (i.e., the group of VCs involved in the company's funding round) (Falconieri, Filatotchev & Tastan, 2019). It has been found that large and diverse syndicates are correlated with lower valuation and correlate negatively with long term stock performance under different metrics. The type of investor, for instance, accelerators, angel investors and VCs were recently tested as predictors of startups' survivability (Choi & Kim, 2018), and variations in the characteristics of VCs (and local factors) were tested as predictors of successful exits (Espenlaub, Khurshed & Mohamed, 2015).

Venture Capital is not the single player in early-stage investment. The role of the angel investor or business angel (BA) is associated with a high volume of capital investment in the USA and Europe comparable to VC in overall size (Wiltbank et al., 2009; Croce, Guerini & Ughetto, 2018). An angel investor – also called a business angel or seed investor, is considered as the very first stage of investments in a venture. That is, the early stage of a private company that occurs right after the founding team has exhausted their personal savings. McKaskill (2009) argues that usually these ventures are not yet developed to stand on their own, nor sufficiently attractive to gain venture capital fundings. For that matter, the angel investors often provide not only monetary capital, but also mentoring (Paul, Whittam, & Wyper, 2007).

Recent studies analyzed qualities of the BAs (Business Angels) as predictors of companies' success (Werth & Boeert, 2013). Using data from Crunchbase on tech startups they find that better connected BAs improve the chances of an exit (IPO or acquisition).

Similar findings have also been obtained in the UK and French markets where BAs are relevant in improving the IPO valuation when compared to VCs (Bruton et al., 2010), although other studies have reported that BA backed IPOs somehow do not perform better than their counterparts (Johnson & Sohl, 2012). Nevertheless, there is enough evidence to consider the presence and traits of BAs (such as links with VC and experience) in the early stage of a VC-backed company as it might impact its valuation (Croce et al, 2018).

2.2. Prior Venture Capital Research Development

Venture Capital has only been noted as a topic of academic research since the late nineties. Harrison and Mason (2019) point out that the 'classic' Venture Capital was first conceived in 1997. For Landström (2007) the scholarly interest in Venture Capital began in the 1970s but reached a pace of only ten papers per year in the late eighties. Several researchers have covered the grounds and evolution of academic VC's research since then.

This research mainly focuses on the better understanding of how VC investments in entrepreneurial companies' work, their choices, contracting conditions, reemployment and growth (Da Rin, Hellmann & Puri, 2013).

Sahlman (1990) provides a useful overview of the structure of the VC industry. Gompers and Lerner (2000) review the literature on VCs up until then. The field has since developed at a very fast pace. Gompers (2007) focuses on some recent empirical work. Landström (2007), Kaplan and Strömberg (2009) look at the literature on buyouts. Metrick and Yasuda (2011) provide a shorter survey of private equity, including both research on VCs and buyouts. Kerr and Nanda (2015) review research on the broader field of entrepreneurial finance but then focus more narrowly on the role of financing constraints.

In Bhidé's (1994) study, it was shown that over seventy percent of all founders had replicated or modified an idea encountered previously. This can be seen as spin-offs. The term "spin-off" can refer to employees starting new ventures without maintaining formal ties to their previous employer or when employees start a new venture and maintain that tie. Gompers and colleagues (2005) showed that around forty percent of all VC-backed founders came from public companies.

Puri and Zarutskie (2012) found that only 0.11% of new companies in the USA created from 1981 to 2005 were funded by Venture Capital. This amount increased to 0.22% over the period from 1996 to 2000. These type of investments are also concentrated in a few high technology sectors with rapid growth opportunities. However, in terms of employment, Puri and Zarutskie (2012) also reported that VC backed companies account for over five percent of employment in the USA, compared to approximately 2.7% for the period between 1981 and 1985. In terms of IPOs, Ritter (2011) showed that between 1980 and 2010, 35% of all USA IPOs were VC backed.

Concerning the choice between Venture Capital and angel financing, Chemmanur and Chen (2014) argue that VCs can add value, but angels cannot. Their model also includes asymmetric information that gets resolved over time, and explains why some entrepreneurs start with angel financing but switch to Venture Capital at a later stage. Schwienbacher (2010) on the other hand argues that angels and VC can both play value-adding roles, but that the key difference is that VCs have sufficient capital to refinance a company, whereas angels do not.

Da Rin, Hellmann, and Puri (2013) noted that there is surprisingly little empirical evidence on the choice between VCs and bank funding. Berger and Schaek (2011) report results from a 2001 survey of small business financing in Italy, Germany, and the UK. They find that 58% of companies obtain bank funding and

6% obtain VC. Their sample comprises SMEs rather than start-ups, with the average VC-backed company being 21 years old. Their main result is that companies that obtain this type of funding may also have a main bank, but that there is a negative correlation between the presence of venture funding and the amount of bank funding.

VC contracts (also called term sheets) have proven to be a rich hunting ground for contract theorists, as reflected by the large number of papers in this area. While VC term sheets contain many clauses, theorists have taken particular interest in explaining the use of convertible preferred equity (CPE henceforth). This security combines a debt like preferred security with an option to convert into an equity-like security. Investors benefit from the preferred terms when the exit value is low (i.e. on the downside) but convert to common equity when the exit value is high (i.e. on the upside). Most theories explain the use of CPE as an optimal incentive structure between entrepreneur and VC.

The entrepreneur typically faces some moral hazard problem, modeled either as private effort or as private benefit. The debt-like claim (on the downside) provides incentives for the entrepreneur to exert effort or exert restraint in capturing private benefits. As active investors, VCs also need to be given incentives, since their actions are by their nature non-contractible (i.e., they cannot be enforced in court). Theories therefore differ mostly in terms of the role of the Venture Capital: some models focus on their effort incentives (resulting in a double moral hazard model); some focus on their decision to refinance or liquidate the venture at an intermediate point in time; and some focus on the VC's control rights (i.e. the rights to exert control over a portfolio company's decision-making) (Bergemann & Hege, 1998; Marx, 1998; Schmidt, 2003; Casamatta, 2003; Cornelli & Yosha, 2003; Repullo & Suarez, 2004; Dessí, 2005; Bergemann & Hege, 2005; Hellmann, 2006).

A key feature of VC financing is that investors can take an active role in the companies they finance. There are two broad types of activities: value-adding services and control actions. The early work by Gorman and Sahlman (1989) and Sahlman (1990) shows that VCs spend a lot of time with their portfolio companies, sitting on the board of directors, mentoring founders, working on raising additional funds, recruiting management and providing strategic analysis.

Lerner (1996) was the first to provide systematic company level evidence on such VC activities. He documents that they increase their presence on the board of directors at the time that companies replace their CEO; They are increasingly likely to take a board seat the higher is their geographic proximity to the company.

Hellmann and Puri (2002) used a hand-collected data set of Silicon Valley companies that contained both VC-backed and non-VC-backed companies (financed mostly by angels and corporate investors). Analyzing several organizational practices, they found that these were associated with a pattern of professionalization. For example, VC-backed companies used more professional hiring practices, were more likely to adopt stock option, and were faster to hire a VP of marketing.

Recently, Nahata, Hazarika and Tandon (2014) mined over 9,000 companies across 32 countries to analyze the impact that institutional and cultural differences and stock market development have on the likelihood of success in the VC investment. They found that these factors have a strong impact in both developed and emerging economies. Moreover, it was noticed that only in developing countries was there no association between local VC and the likelihood of investment success. The writers argue that this is due to the lack of experience and expertise in developing countries.

2.3. Theories Applied to Venture Capital Research

Cornelius and Persson (2006) showed that the VC research community is mainly divided into two separate clusters based on their research approach. The first one has a background in finance and economics and mainly analyses Venture Capital on a macro level, using a financial approach, such as agency theory, game theory, capital market theory, the resource and efficiency market approach and so on as theoretical frameworks in their studies, which are published in financial and economics journals.

The other cluster of researchers has its origins in management and entrepreneurship research and for this reason have strong managerial bias and heterogeneity of paradigms and approaches.

As shown in Table 1, many theories have been considered when trying to better understand VC markets. We have arranged them according to their level of financial versus managerial approach. For example, the first three theories have a stronger financial approach, while the last three have a higher managerial one.

However, some of these financial approaches are controversial. This is due to Venture Capital markets being very diverse from the financial market in several respects, thus making it hard to implement these models in a market that deals with young firms, lacks efficiency in exits and IPOs and has low to no performance history or financial information.

Table 1 -Theories and Research on Venture Capital organized according to their closeness to Financial or Managerial Research. Created by the authors, 2022.

Managerial < ---> Financial

Theory	Notable Researchers
Agency Theory	Landström, 1992; Robbie, Wright, & Chiplin,1997; Van Osnabrugge, 2000; Arthurs & Busenitz, 2003; Panda, 2018; Gompers, 2022.
Game Theory	Cable & Shane, 1997; Elitzur & Gavious, 2003; Fairchild, 2011; Zarei, Rasti-Barzoki, & Moon, 2020.
Resource Approach	Lockett & Wright, 1999; Battisti et al, 2022.
Population Ecology	Sapienza, Amason, & Manigart,1994; Bertoni, Colombo & Quas, 2019.
Institutional Theory	Fiet et al., 1997; Karsai, Wright, & Filatotchev, 1997; Ahlstrom & Bruton, 2002; Busenitz, Fiet, & Moesel, 2004; Manigart et al., 2002; Isaksson et al., 2004; Bruton et al., 2005; Bruton et al., 2010.
Network Theory	Bygrave, 1988; Ahlstrom & Bruton, 2006; Abell & Nisar, 2007; Ferrary & Granovetter, 2009.
Signal Theory	Köhn, 2018; Löher, Schneck, & Werner, 2018; Nigam, Benetti, & Johan, 2020; Gloor et al., 2020.
Social Exchange and Trust Theory	Sapienza & Timmons, 1989; Sweeting, 1991; De Clercq & Sapienza, 2001, 2005 & 2006.
Social Capital Theory	Morgan & Hunt, 1994; Maul, Autio, & Murray, 2003; Weber & Weber, 2007.
Knowledge and Learning Theory	De Clercq & Sapienza, 2005; Chen, Nguyen, & Ha, 2022.
Cognition and cognitive bias Theories	Parhankangas & Landström , 2006 Souakri, 2020.
Procedural Justice Theory	Sapienza & Korsgaard, 1996; Busenitz et al., 1997; Sapienza et al., 2000; Sørheim, 2012.

Recently, many author have also worked with a new theory called ‘finance of innovation’ and linked it to VC research. We will also briefly discuss this theory and its outcomes next. A brief explanation of the main theories used in this research and how they relate to Venture Capital research is also addressed.

2.3.1. Knowledge and Learning Theory

Knowledge Theory states that experience can be thought of as knowledge accumulated through learning. Organizations, in these case companies, are seen as constantly learning from their own history by encoding inferences into habits and routines that guide their behavior and decision making (Levitt & March,1988).

In this sense, it is plausible to state that companies who have greater knowledge about a niche are going to have greater prospects within this niche. This is because the knowledge that firms accumulate through learning are path dependent, meaning they will differ between a firm which has greater experience and one with less experience.

Since knowledge comes from experience and is accumulated over time, it is reasonable to argue that older and more experienced VC companies have higher chances to have greater investment success. Even though it is not yet clear if this relationship is due to excellence in the selection process of companies with the most prosperity potential or due to the company's active role in the process of the invested company's growth, as constantly happens with VCs that desire to monitor managers closely or even be part of the company's management team.

We argue that this theory can also be applied to venture capital backed companies' experience – i.e., CEOs/management teams with more experience of startups may be expected to have a higher chance of success. This association has been raised before by Milosevic (2018). The author investigated the relationship between the professional experience and education of VC firms and found a positive relationship between human capital variables and successful exits of VC backed companies. However, their findings suggested there was no significant correlation between human capital and fundraising activity.

2.3.2. Signal Theory

In a market considered efficient, information must be available to all rational agents, so that they can make the best possible decisions in order to maximize their profits. Thus, with the objective of reducing information asymmetry, companies voluntarily disclose information to their current and potential investors (Dainelli, Bini, & Giunta, 2013).

This behavior is explained by Signal Theory which was developed to help explain how decision makers interpret and react to situations in which the available information is incomplete and asymmetrically distributed among the agents of a market (Spence, 1973). According to this theory, companies have incentives for the incremental disclosure of information, in order to reduce information asymmetry (Beyer et al., 2010). Thus, signaling theory postulates a positive relationship between the performance of a company and the amount of information disclosed to the market (Janiszewski et al., 2017).

Signaling information is also present in the VC market. Löher, Schneck and Werner (2018) state that to reduce the informational gap, founders of high-quality start-ups will send quality information via signaling which indicates that they will run their new venture successfully. Quality signals are expected to play a crucial role in investment decisions.

Another example is in the research of Gloor et al. (2020). Using signal theory these authors found that startups whose board members were active on Twitter attracted additional funding over the years.

VC backed companies lack financial informational. Thus, the market has a high degree of information asymmetry. VCs confronted with this information asymmetry are likely to look for certain signals to reduce the informational gaps, and better exercise their judgement to fund the most promising ventures.

2.3.3. Network Theory

Network Theory (also called networking theory) has an extremely wide field of application. Since the 1970s, it has given notable contributions to areas ranging from mathematics, programming, biology, economics, social science, to fashion. It helps in the understanding of both the spread of diseases as well as the rapid trends of fashion (Linn, 1999).

Burt and Celotto (1992) explain that networks create social capital for individuals, helping to build trust and increase bonds between parties. In doing so, networks can create a locus of innovation in high-technology industries, including “innovative regions” such as Silicon Valley (Fleming & Frenken, 2007).

Regarding investments and Venture Capital markets, Network Theory has the purpose of identifying the role of a simple link between parties and their influence on the decision-making process.

Based on empirical evidence from China, Huang, Lai, and Lo (2012) demonstrate the mediating role of business networks in the relationship between founders' ties and human capital, and both organizational innovation and firm performance.

In the same direction, Nigam, Benetti, and Johan (2020) found that social media networking has the strongest impact on access to funding capital. This is also the case for a study carried out in the Malaysian market (Narayanasamy, Hashemoghli, & Mohd Rashid, 2011), which suggests that both the VCs and the invested companies' networking plays a big role in shaping their prospects.

2.3.4. Institutional Theory

Institutional Theory asserts that a market's environment can strongly influence an organization and its structures through isomorphism. Characteristics that differ from optimal rationality may play a role in the conventional behavior within the social group to which entrepreneurs may belong.

In the VC market, institutional theory is often used to explain the highly standardized behavior among different subgroups of venture capital firms. For instance, Zacharakis, McMullen, and Shepherd (2007) found that venture capitalists from different countries use different information when formulating their decisions.

Garry B. Bruton is one of the main contributors to the academic research on institutional theory in VC markets. Bruton et al. (2010) state that although institutional theory is an increasingly utilized theoretical lens for entrepreneurship and has proven itself highly useful, there is still a need to establish a clearer understanding of its effects.

2.3.5. Agency Theory

Agency Theory focuses on the conflict of interests between the principal – capital owner and the agent – managers and decision makers within a company. This conflict occurs due to their asymmetric access to company information, creating room for manipulation. That is, in a situation where an agent is contracted to run a firm and make decisions on behalf (and, hopefully, in their best interests) of a principal, information asymmetries are prevalent between the parties (Mitnick, 1975).

Regarding our study, the principals are the Venture Capital companies that own the resources that are going to be invested in VC backed companies. On the other hand, the VC backed companies are the agents – those who receive VC funding and hold the influence of decision-making as well as having better knowledge about the company's inside information.

These decision makers may not always act in the best interests of the capital owners. The principal knows about this possibility and will try to mitigate it as much as possible, holding back relevant investment to do so.

Agency Theory has already been applied in the VC context. Van Osnabrugge's (2000) study has demonstrated how agency theory can be utilized to understand governance issues in VC firms. They show how VCs may behave differently in their investment processes on account of different agency risks. Nitani, Riding, and He (2019), among different theoretical approaches, also use the agency theory perspective to explain the VC market. They find that crowd investors reduce agency risks by choosing larger firms managed by experienced and educated managers.

2.3.6. Finance of Innovation

Finance of Innovation is a field that deals with the specific financial matters within innovative markets and products. Although considered by some a theory, it is a field that has not only been applied to Venture Capital per se, but also to all innovative processes. It is a fairly new concept and for this matter it still struggles with a wide acceptance of its theoretical validity and contributions.

It differs from traditional finance which deals with non-innovative products, like credit and insurance. As stated by Bottazzi and Da Rin (2002, p. 229): "Venture capital is considered to be the most appropriate form of financing for innovative firms in high–tech sectors."

The innovation process has its own characteristics, which may suggest an important and underexplored area, with potentially deep implications for theory. Kerr and Nanda (2015) point out four different features of innovation: the innovation process is inherently uncertain – and uncertainty is fundamentally different from risk; the challenge of making investments in the face of extreme uncertainty is that the return from the innovation process is concentrated in a minority cluster of successful companies, departing from the usual Gaussian or normal distribution – much like the wealth distribution; a high degree of information asymmetry exists between the founder and the VC, that is, there is no financial information to mitigate asymmetry, and; there is a high percentage of intangible assets.

3. Venture Capital Worldwide Market

Academic literature points out a link between Venture Capital and the finance of innovation, in the sense that it focuses on the existence of non-financial value added through the VC active ownership of a venture's share (Metrick & Yasuda, 2011; Rossi, Thrassou, & Vrontis, 2011).

In this way, Finance of Innovation complements both knowledge and networking theory but differs from them in the sense that it has the purpose of investigating the additional value that a VC may add to one of their investees/active ownerships to the detriment of the others with no active ownership.

Tjade and Thrane's (2010) findings show that ventures with active VC ownership typically experience more value added than some essential venture capitalist activities, such as replacing management or inputs on new business developments.

This market effect is also seen within all types of venture investors, not only CVCs. If we take a look at all venture capital funding, current data for the last couple of decades shows notably the same effect. There is a retraction of new venture investments whenever the whole stock market crashes.

Figure 1 - New venture capital funding per year. Source: Created by the authors, data from CrunchBase, 2022.

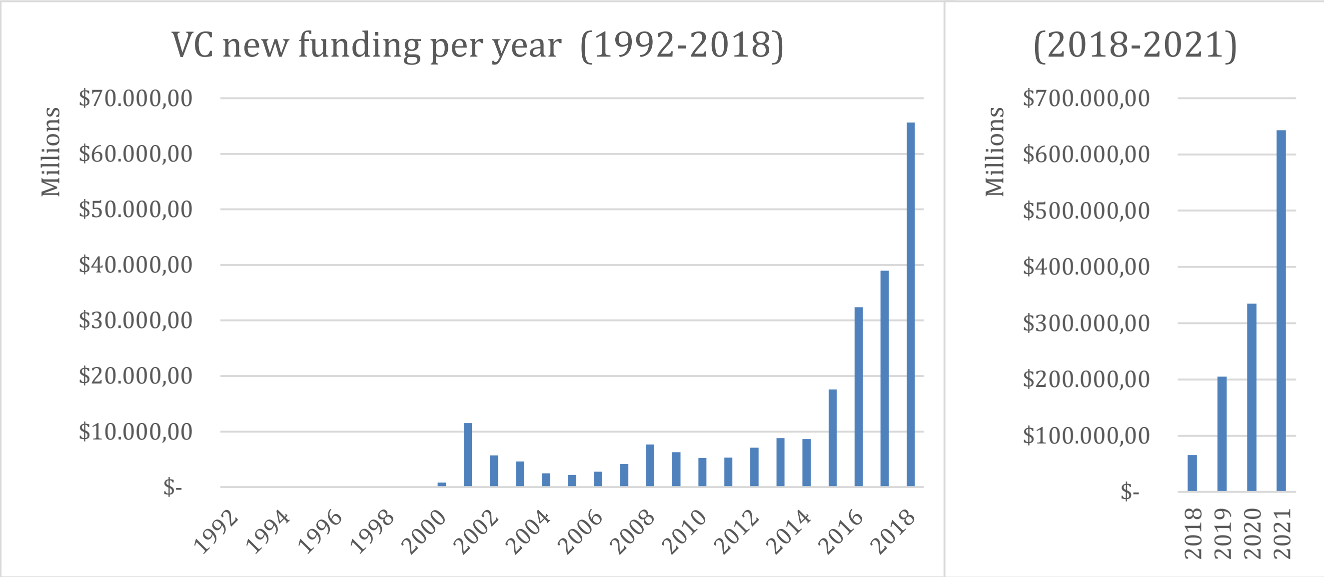
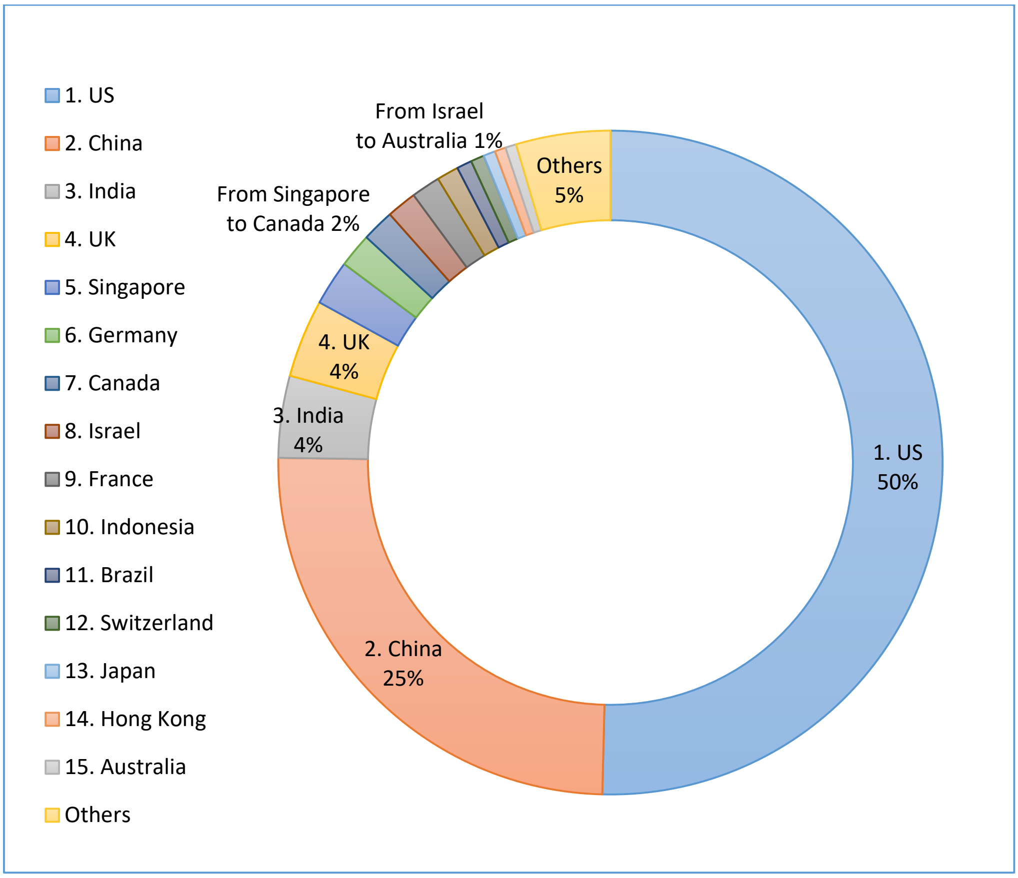


Figure 1 shows the data on all types of venture capital investors from year 1992 to 2018, and then with a greater scale, it shows from 2018 to 2021. Notice that 2018 is shown both in the first scale and then it is repeated in the second, this was intended to demonstrate how the VC market has been rapidly growing.

Venture Capital investments grew intensely in 2018 and 2019, with a total of over sixty billion dollars in 2018 and over two hundred billion dollars in 2019. The Covid-19 crisis did not have a noticeable impact on the VC's rising market as well, with the market continuing to rise. In 2020, there was a total of more than three hundred billion dollars of new capital injected into the VC market worldwide, and in 2021 this number doubled, with a total of new capital above six hundred and forty thousand billion dollars. Just the amounts raised in 2020 and 2021 by themselves represent more than all the VC market has ever raised since the 1960s. The fact that the market grew in 2020 and 2021 during the Covid-19 crisis may be considered a surprise. However, we can speculate that this reflects a growth in technology companies, who benefited from the impact of the pandemic on global tech and online trade.

Figure 2 - Total VC Capital Founding per Country. Source: Created by the authors, data from CrunchBase, 2020.



The VC market is indeed showing its growing potential, especially in the last few years. The distribution of VC funding is mainly concentrated in the US and China (Figure 2), accounting for 75% of the total worldwide investments. Note that emerging markets represent a very small proportion of the worldwide amount (Figure 2 and Table 2).

Table 2- Total VC Capital Founding per Country. Source: Created by the authors, data from CrunchBase, 2020.

Position	**Country**	**Amount of Funding (in Billions of Dollars)**	**Percentage**				
1	US	457,98	50,39%	31	Argentina	0,62	0,07%
2	China	225,72	24,84%	32	Argentina	0,61	0,07%

3	India	36,26	3,99%	33	Poland	0,60	0,07%
4	UK	34,50	3,80%	34	New Zealand	0,58	0,06%
5	Singapore	19,93	2,19%	35	Estonia	0,53	0,06%
6	Germany	15,12	1,66%	36	Nigeria	0,49	0,05%
7	Canada	14,31	1,57%	37	Thailand	0,48	0,05%
8	Israel	13,31	1,46%	38	Vietnam	0,45	0,05%
9	France	12,80	1,41%	39	Turkey	0,44	0,05%
10	Indonesia	9,66	1,06%	40	Others	0,44	0,05%
11	Brazil	6,70	0,74%	41	Portugal	0,39	0,04%
12	Switzerland	5,95	0,65%	42	Lithuania	0,34	0,04%
13	Japan	5,27	0,58%	43	Norway	0,33	0,04%
14	Hong Kong	4,86	0,53%	44	Egypt	0,25	0,03%
15	Australia	4,79	0,53%	45	Hungary	0,23	0,03%
16	Spain	3,86	0,42%	46	Chile	0,23	0,03%
17	South Korea	3,44	0,38%	47	South Africa	0,19	0,02%
18	The Netherlands	3,36	0,37%	48	Czech republic	0,18	0,02%
19	Ireland	2,62	0,29%	49	Saudi Arabia	0,17	0,02%
20	Sweden	2,59	0,29%	50	Bangladesh	0,14	0,02%
21	Belgium	2,22	0,24%	51	Latvia	0,11	0,01%
22	Colombia	1,98	0,22%	52	Ukraine	0,11	0,01%
23	Finland	1,72	0,19%	53	Jordan	0,10	0,01%
24	Mexico	1,70	0,19%	54	Cyprus	0,10	0,01%
25	Russian Federation	1,66	0,18%	55	Romania	0,04	0,00%
26	Africa	1,54	0,17%	56	Peru	0,04	0,00%
27	Denmark	1,33	0,15%	57	Uruguay	0,02	0,00%
28	Taiwan	1,32	0,15%	58	Costa Rica	0,01	0,00%
29	Italy	1,24	0,14%	59	west bank	0,01	0,00%
30	Austria	0,90	0,10%				

In Table 2 we provide a ranking of all countries' concentration of funding capital (in billions of dollars). We can clearly see how the US alone is of great relevance to this market, having over half of all the market. Brazil stands in eleventh place with 0.74% of the VC market share.

4. The Brazilian Market

Brazil is still a developing country. It has few publicly traded companies, which makes academic valuation's mainstream models not as incisive as they are in other more efficient markets such as the USA, for instance. At the same time, constant growth in worldwide technology has lowered the barriers for innovation and has stimulated new startup companies with high expectations in developing countries like Brazil.

Regardless, academic research in Brazil still mainly focuses on publicly traded companies and literature on private equity and venture capital is scarce, maybe due to data access struggles – as stated by Gioielli, de Carvalho, and Sampaio (2013). Using a sample of 463 companies from Crunchbase, a database of VC-backed companies, it was found that the typical investment bands for the raised capital are US$ 100K-1M, US$ 1M-10M and US$ 10M-100M, respectively (Gereto, 2019). The main exit strategy is acquisition, typically associated with large international enterprises expanding into Brazil.

Nahata (2008) examine Brazilian data between 1996 and 2002 and find only 189 VC backed companies, of which only 22 had a successful exit. VC investments in Brazil have only started to take on more prominence in the last couple of years.

In 2018, there were 356 unicorn companies worldwide. Unicorn is the title given to private capital companies with market value over one billion dollars. Nonetheless, Brazil had almost no role in the ‘unicorn’ world, with as little as only one unicorn, although a very notable one, fintech online banking organization, Nubank (which went public in December 2021 in the NYSE). The country also had a low attractiveness of investment ranking, taking 54th place, as shown by the Venture capital & private equity country attractiveness index, provided by IESE Business School (2019).

Nevertheless, a year later, the acceleration rate of new unicorns placed Brazil together with top world leaders, leaving behind some prominent countries like the UK, Israel and India. Next to Germany, and right after China – with 22 converted unicorns, and the US – with the leading 78 converted unicorns, Brazil took third place in 2019 in terms of the number of companies that had converted to unicorns. (IESE annual report, 2019).

This shows that 2019 was a good year for the Brazilian startup ecosystem and maybe a start of a new era in Brazil's representation in this market. Five new unicorns rose: Gympass, EBANX, QuintoAndar, Loggi and Wildlife. Early in 2020, Loft – a company innovating in the real estate property market, and Ifood – food delivery company, joined the exclusive unicorns group. By the time all of this was happening, Nubank already was worth over ten billion dollars (LABS, 2019).

There are currently hundreds of thousands of unicorn companies worldwide. Valuation in these types of companies is somewhat controversial, as discussed before, but if we take a look at the VC backed companies' total founding amount, we can have a more objective perspective on the VC market. Today we have over 30 thousand companies worldwide that have been invested with over one million dollars. Only in Brazil there are currently 224 of these companies. Brazil today occupies the 11th place in total funding amount. There are currently over one thousand PEVC (Private Equity and Venture Capital) backed companies in Brazil, over one thousand seed, early-, and late-stage ventures and over two hundred of them have already raised over one million dollars.

5. What is Success in the VC market?

As mentioned above, a great deal of research has made use of the word 'success' in the venture capital market as a way to overcome the lack of market value and financial information in this area of business models. For example, see Gompers and Lerner (2000), Hochberg, Ljungqvist and Lu (2007), Sorensen (2007, 2008), Nahata (2008), Gompers et al., (2008), Zarutskie (2007), Brander, Amit, and Antweiler (2002), Cumming and MacIntosh (2003), Nahata, Hazarika, and Tandon (2014), Humphery-Jenner, and Suchard (2013), Milosevic (2018) and Nanda, Samilab and Sorensonc (2020).

Unfortunately, though, the field does not share a common understanding of what success is and how it is defined and measured. Some of the main definitions used by academics are examined next.

5.1. Exit events as success

Tykvová (2018) uses the exit event to distinguish between successful and unsuccessful investments. The author used data from 8270 venture capital backed companies from 41 countries, defining the ones that had exited (IPO or investment round) from 2009 to March 2013 as successful ones, and all others as unsuccessful. With this approach, the research finds a positive correlation between international VCs and success. It is argued that these may mitigate the negative effects that inefficient legal environments in investment countries have on companies' success, thus supporting the view that the involvement of international VCs is conducive to success. It further attributes this effect to the benefits that international VCs offer their portfolio companies, such as richer experiences, combined with access to broader networks and/or to foreign product, capital, and exit markets.

Nahata (2008) uses a similar approach to define the dependent variable of 'success', using an investment sample from late 2001 to early 2006 and the time period in which exits were analyzed. All companies that had not exited successfully by the beginning of 2006 were labeled as unsuccessful exits.

Streletzki and Schulte (2013) added another condition to this 'exit or not' method. They did not consider success as defined by any profitable exit, but rather only by high-flying ones. High-flyer exits are in general those exits that multiply the VC invested by a factor greater than 5 or 10. The data used was 64 ventures from eight German VC firms. Ten of the 64 exits were classified as high-flyers, while 54 ventures reached a lower exit multiple than five. Their findings point out three high-flyer predictors: company, product and market related. A concerning problem with this method is that it varies depending on the company's sector, and on the country's economy.

5.2. Success as survivability

A second common definition of success relates to a venture capital backed company's survivability - that is, years functioning in the market. Cooper, Folta, and Woo (1995) define their dependent variable, that is 'start-up success', as survival after 2 or 3 years. Clarysse, Bobelyn, and del Palacio Aguirre, (2013) use this approach of survivability over time but also point out that the validity of this assumption is often questionable as the impact of many covariates are clearly time dependent.

They evaluate the extent of VCs' contributions to 206 venture-backed UK companies, especially the potential trade sale of their portfolio companies. They conclude that working with experienced VC firms is beneficial for portfolio companies aiming for a trade sale. If a VC firm has realized one or more trade sales before, this significantly increases the probability that the portfolio company will be able to realize a trade sale in the current situation. Three types of (congenital, experiential and vicarious) learning of the VC firm significantly contribute to the likelihood of a trade sale of its portfolio companies. They also show that congenital experience makes no significant contribution to the hazard of being acquired (Clarysse, Bobelyn, & del Palacio Aguirre, 2013).

McKay and Chung's (2005) conceptual framework of Venture Capital's success is another example. Although not an empirical research, and entrepreneurs' success is not directly defined, they make a case for it having a link with the company's survival.

Kerr, Lerner, and Schoar (2014) find that financing by angel investor groups is associated with improved likelihood of survival for four or more years, higher levels of employment, and a higher likelihood of undergoing a successful exit (both IPO and/or acquisitions).

Witt (2004) comments that survivability is a prominent, non-subjective, company-related measure of a start-up company's success, and that data on this success measure can be obtained comparatively easily. Given the founding date of a start-up in a sample of founded companies, researchers can investigate for each sample firm if it still exists at the time of the inquiry. This can be done by calling the company, visiting it personally, or visiting its web site. To eliminate biases owing to diverse survival periods, the sample could consist of only those start-ups that were founded in the same year. Analysis could then show how long individual firms have survived and which start-ups left the market after what time periods.

Baluku, Kikooma and Kibanja (2016) measure success based on a score created with four different factors: financial rewards, survival time, owner's satisfaction and generated employment. Their findings show that among the five factors of psychological capital, optimism tends to be the most important contributor to entrepreneurial success. Individuals with high startup capital and a high level of optimism have better chances of entrepreneurial success. While success in entrepreneurship may depend on several factors, it is clear from this study that individuals with high startup capital are more likely to succeed in entrepreneurship. However, those with a high amount of psychological capital have better chances of success, and the odds of success are even higher when one has both high startup capital and a high level of optimism.

5.3. Success as amount of funding capital raised

A third group of researchers fall back on the capital raised, that is, the total amount of funding, as an indicator of a venture's success. This is due to the fact that startups' success rates and development are to a great extent dependent on their access to capital.

Walske, and Zacharakis (2009) define success as a Venture Capital backed company's ability to raise subsequent venture funds. They state that raising subsequent funds is a strong proxy for fund performance, because VCs make the decision to participate in a new fund based on the performance of previous funds (Cumming, Fleming, & Suchard, 2005). They also note that the ideal approach would be relative to revenue information, but unfortunately, this type of performance data was only available for 20% of the Venture Capital Funds (VCFs) in their sample. Therefore, they used a ratio-scale metric variable that reflects the number of subsequent funds raised by each VCF, 10 years post the firm's founding date.

They found that VCFs founded by those having prior Venture Capital or senior management experience were more likely to raise subsequent venture funds. Venture capital experience had a higher chi-square than senior management experience, showing that it is slightly more explanatory in predicting nascent VCF success. Consulting experience also aids VCF performance. VCF founders with entrepreneurial experience were less (negative correlation) likely to raise follow-on funds. This is a bit counterintuitive, and the authors have addressed this recalling the concerns expressed by the Limited Partners during their interviews about an entrepreneur’s ability to manage a portfolio of companies. They state that: ‘being a good VC is not about just picking and developing one or two good ideas, but managing a portfolio of investments while simultaneously diversifying risk’. Neither technical experience nor financial experience was found to have a significant effect (Walske & Zacharakis, 2009)

Prohorovs, Bistrova, and Ten (2018) define success as attracting financing at the initial development stage, that is, fundraising. They interviewed 40 founders, where 15 managed to attract capital and 25 failed. Based on the analysis conducted, it was concluded that companies which tend to be more successful in attracting seed funding are managed by entrepreneurs who have had previous experience in creating business entities and are capable of building a team with employees who have appropriate experience, specialized education and high-level management skills. Note that this result is opposite to the previous ones, by the authors Walske and Zackarakis (2009). The most common obstacle in the capital attraction process is lack of professionalism of the team, which confirms the evidence found in the scientific literature

5.4. Self-reported and self-developed scales of success

Another set of methods that was found to be widely used in order to assess a venture firm’s success was the use of self-developed scales and self-reported success (Sapienza & Amason, 1993; Kessler, 2007; West & Noel, 2009; Weber & Weber, 2010; Kuckertz & Kohtamaki, 2010; Streletzki & Schulte, 2013; Tinkler et al., 2015; Harrison, Mason & Smith, 2015; Baluku, Kikooma & Kibanja, 2016).

While a vast amount of research makes use of this procedure the scales used by them are still not validated by academics, nor were most of the scales pre-tested before conducting the research. Not only is that in itself troublesome, but when we look closer at how each scale was built, we find a vast variety of concepts and presumptions that can lead to contradictory conclusions about a singular phenomenon.

For instance, while West and Noel (2009) measured success by subjective assessment based on three questions directed to the entrepreneurs: their percentage of ideal performance being achieved, and two questions concerning their overall performance compared to other similar companies; Tinkler et al., (2015) used hypothetical firms and investors to measure evaluations about the venture's potential for success, asking participants to rate the company on a 6- point scale. Example questions included "how unique is the company's product?", "how interested would you be in buying the company's product?", and "how likely would you be to schedule a meeting with the company's founder to learn more about the venture?". They constructed a composite "optimism for the venture" scale with combined question sets by creating scenarios of business opportunities and asking participants which ones they were more likely to invest in.

We will return to this topic in Chapter 2, where a more detailed, fine-grained analysis will be presented.

6. Conclusion

This chapter was devoted to presenting a landscape of both Venture Capital markets and research, as well as charting how research into this topic has progressed over time from its early origins. It was not our intent (nor would it have been possible) to thoroughly review all the works and literature on the Venture Capital phenomenon.

We instead broadly remarked on the history of Venture Capital development, pointing out how the relevance of venture capital has increased over the decades - rising both in contribution to the world's technological development as well as raising a greater volume of capital over the years. We also showed that Venture Capital is a market that is spreading worldwide, reaching developing countries in recent decades.

Another contribution of this chapter was to point out some of the main theories used in the literature of Venture Capital. We showed that numerous theories have been applied; some have deep roots in economics and finance, and some are mainly managerial, but only a few of them could be argued to have been developed with Venture Capital in mind.

Our review has raised a series of considerations and insights that may be pursued in further research. For the most part, these insights do not represent single, specific areas of investigation but rather wide approaches that were found to be in need of more research attention. General suggestions are pointed out – such as the lack of a conceptual framework, theory, and especially a common language. These topics are further addressed and elaborated upon in Chapter 4.

CHAPTER 2

STUDY 1: Definition of Success within the Venture Capital Market: A systematic review.

1. Introduction

This research aims to systematically review the academic literature, with the aim of understanding how *Success* is defined within the Venture Capital market and related research field.

Publicly traded companies are the focus of valuation models, which have been extensively studied and improved, such as the residual income valuation (RIV), discounted cash flow (DCF), multiperiod valuation models based both on RIV and DCF, price-earnings ratio models, and so on (Kleidon, 1986; Barker, 1999; Koller et al., 2000; Palepu et al., 2000; Penman, 2001; Demirakos, Strong, & Walker, 2004)

These valuation models require reliable and accessible financial information. Crucially, although this information is available within already ongoing functioning companies, this is not the case for private ones, especially new companies like start-ups and other VC backed firms. This is due to the Venture Capital market being very different from the financial market in several aspects, thus making it hard to implement these mainstream valuation models in a market that deals with young firms, lacks efficiency in exits and IPOs and has low to no performance history or financial information.

This leaves a gap in our understanding of how to measure expected future financial performance of what today can be only an idea. Due to the misfit with traditional valuation methods, ‘success’ has been frequently used as a criterion to fill this gap. Many researchers have relied on assessing a venture’s success to determine what are the circumstances that make it possible for a new venture to rise, while others do not.

Although an interesting way to overcome the lack of financial information, there still is not a universal definition of a venture’s ‘success’, or their ‘performance’ measurement. This leads to different approaches and understandings; from years of a venture firm's survivability, amount of funding capital raised, number of employees, to self-reported success, there are a wide variety of disparate academic understandings of a venture's success.

This can be problematic, as research findings can be directly linked to their prior definition of success. Our aim is to systematically review empirical papers that have adopted *success* as their dependent variable, investigating what their definition of success was and their research's subsequent outcomes and results. We argue that different definitions of success may lead to controversial results that may not be due to the market's characteristics per se, but merely to one's prior definition and understanding of what constitutes success.

2. Literature Review.

As we have argued above, how to value a company is traditionally a finance topic that involves financial information and market value. Most financial valuation methods were developed for well-established companies and especially for companies in the more efficient public capital market.

As stated by Milosevic (2018), it would be ideal to measure performance by the returns of VC firms. However, VC firms are quite reluctant to disclose their returns publicly. Additionally, the Venture Capital market deals with the additional uncertainty created from a startup's inability to provide statistically reliable accounting information. In this case, it is not possible to apply usual valuation techniques usually designed for publicly available companies with full information disclosure.

Miloud, Aspelund, and Cabrol (2012) argue that valuation methods fail to yield consistent results because these methods require accounting information that a new venture typically cannot provide. As also demonstrated by Korteweg and Nagel (2016), the traditional financial methods yield valuations with large variability. This happens because young firms lack financial information.

For this matter, a great deal of academic research has considered other approaches to gain information on the venture's value.

An alternative used in these situations is pricing based on inputs - such as entrepreneurs' qualities and expectations, market attractiveness, cutting edge products, etc. Here academics and practitioners have often used the term 'Success' and 'Success factors' to fill in the gap made by traditional valuation methods, which is given as a better alternative to purely 'guessing', 'gut feeling', or intuition.

Baluku, Kikooma and Kibanja (2016) show that there are no globally agreed-upon indicators of entrepreneurial success. Moreover, the authors state that future research should focus on developing widely acceptable inventories for measuring entrepreneurial success.

Brush and Vanderwerf (1992) argue that the definition of success depends on the company's state of development in the foundation process, and that there are very different possibilities to define it. For instance, a first suggestion for a success measure is the completion of the idea and planning phase. Imagine that the founder has moved from pure ideas, has developed a business plan and has formally developed a business start-up. The fact that the firm has been able to move to this next stage may be considered a success, although it is not an overly restrictive/stringent success measure.

Witt (2004) reviews empirical studies on the network success hypothesis and makes clear that studies have rarely come up with significant results. He explains that this surprising evidence can be explained by large differences in the way that the dependent and the independent variables were defined and by the effects of unobserved variables such as the networking expertise of the founders and the entrepreneurs' level of existing know-how in the areas of cooperation and networking.

New venture companies in developing countries have it even harder, for there is a mismatch between the increase in entrepreneurial activities and an unfit low rate of success (Gindling & Newhouse, 2014). This phenomenon has largely been attributed to a lack of access to initial financial capital, which forces new entrepreneurs to start their ventures without the ideal conditions to make it through – with low or no resources available. This generally low amount of startup capital negatively affects success (Merz, Schroeter, & Witt 2010).

We can see clearly that studies have sought to overcome Venture Capital valuation issues by using and analyzing the ‘Success’ of VC investments: Gompers and Lerner (2000), Cumming and MacIntosh (2003), Hochberg, Ljungqvist and Lu (2007), Sorensen (2007, 2008), Nahata (2008), Gompers et al., (2008), Humphery-Jenner, and Suchard (2013), Nahata, Hazarika, and Tandon (2014), Milosevic (2018) and Nanda, Samilab and Sorenson (2020). This leads us to our research questions.

Our research questions are as follows.

First Research Question: How have academics defined success, that is, how have academics defined and measured the success of venture Capital backed companies in their empirical studies?

This question leaves us with another relevant consideration. If there are indeed different definitions and operationalizations of a venture capital backed company’s success, then how does this affect the results of studies that have relied on different approaches? More specifically, does the lack of a common language lead to conflicting results? With these questions in mind, our second research question is as follows.

Second Research Question: Do different definitions of success lead to conflicting results? That is, how do the predictors of success identified in empirical research differ depending on the definitions/operationalizations of success adopted by the studies’ authors.

With both of these questions we aim to gain a better understanding of the Venture Capital market, as well as to offer a common language with which to discuss key issues within the field.

3. Methodology

The aim of this research is to assess the available literature that focuses on the understanding of Venture Capital backed companies’ success factors, on how they assess their potential, and their future prospects. Having ‘success’ as the main object of our research, we also aim to gain a better understanding of how a VC-backed firm's success is perceived within academic research. Among the literature that aims to better understand VC backed firms, different definitions of 'success' may shape the results of their 'factors' of success. We argue that the lack of a universal definition of a VC backed firm's success may create an academic environment of contradictory findings and noise. We thus aim to contribute to a better understanding of how to assess tangible means of measuring a market that lacks the traditional financial information that traditional Valuation has access to.

According to this objective, we propose that an effective way to address this problem is by carrying out a systematic review that will examine the literature on this matter. A systematic review "is a specific methodology that locates existing studies, selects and evaluates contributions, analyses and synthesizes data, and reports the evidence in such a way that allows reasonably clear conclusions to be reached about what is and isn't known" (Denyer & Tranfield, 2009, p. 671).

Systematic reviews "provide the basis for planning and interpreting new primary research. It may not be a sensible use of resources and in some cases, it may be unethical to undertake research without being properly informed about previous research" (Gough, Thomas, & Oliver, 2012, p.3).

3.1. Selection of Articles

Our first concern was to exhaustively include all the relevant studies. This is essential in order to avoid bias from study selection (Gough et al, 2012). That is why we chose to simultaneously search multiple different search databases.

Seven different search procedures were carried out using four different academic databases for this systematic review. The four academic databases we used were Periódico Capes, Jstor, Taylor and Francis Online, and ProQuest. All of these search processes, their volume of outcomes, and refining procedures are described next:

- Search database: Periódico Capes
  Search term: 'venture capital' = 47,538 results.
  Search terms 'venture capital' and 'success factors' = 1,056 results.

Filter only in the papers' abstract: 41 results.
Filter: only peer reviewed papers = 17 results.

- Search database: Jstor
  Search term: 'venture capital' = 18.825 results.
  Search term: 'venture capital backed' = 498 results.
  Search terms: 'venture capital backed' AND 'success' = 329 results.
  Search terms: 'venture capital backed' AND 'success factors' = 15 results.
  Filter: only peer reviewed papers = 13 results.
  The 13 articles were from:
  Biological Sciences (1), Business (9), Economics (9), Finance (3), Management & Organizational Behavior (4), Technology (1)
  Biological Sciences and General Science were excluded as the content of the articles was divergent from our research purposes.
  Final total articles from Jstor: 12 results.

- Search database: Taylor and Francis Online:
  Search term: 'venture capital' = 419 results.
  Search term: 'venture capital backed' = 284 results.
  Search terms: 'venture capital backed' AND 'success factors' = 1 result.
  Search terms: 'venture capital' AND 'success factors' = 18 result.
  Search terms: [All: 'success factors'] AND [All: 'valuation'] AND [All: 'empirical'] AND NOT [All: 'tax'] AND NOT [All: 'crowdfunding']
  Filter: only peer reviewed papers = 13 results.
  This gave us 13 additional papers.

- Search database: Proquest:
  Here we made three different searches, as follows.

1. First search in Proquest for term 'venture capital' in the title OR 'venture capital' in the thesaurus = 365,9991 results.
   Search in Proquest for term 'success factors' in the title OR 'success factors' in the thesaurus = 33,475 results.

Combined search terms ‘venture capital’ in the title OR ‘venture capital’ in the thesaurus AND ‘success factors’ in the title OR ‘success factors’ in the thesaurus = 167 results.
Exclusion/inclusion filters applied: ‘peer reviewed’ ‘scholarly journal’ ‘proquest one business database’ excluding papers with a biotech focus = 62 results.

2. Second search in Proquest for term ‘venture capital backed company’ in the title OR ‘venture capital backed company’ in the abstract OR ‘venture capital backed companies’ in the title OR ‘venture capital backed companies’ in the abstract = 8,350 results.
   Search in Proquest for term ‘success’ in the title OR ‘success’ in the abstract OR ‘success’ in the thesaurus OR ‘success factors’ in the title OR ‘success factors’ in the abstract OR ‘success factors’ in the thesaurus = 1,787,196 results.
   Combined search terms using AND = 391 results.
   Exclusion/inclusion filters applied: ‘peer reviewed’ and excluding 2 biotechnology-oriented papers = 30 results.

3. Third Search in Proquest for term ‘venture capital backed’ in the title OR ‘venture capital backed’ in the abstract = 11,211 results.
   Search in proquest for term ‘success’ in the title OR ‘success’ in the abstract OR ‘success’ in the thesaurus OR ‘success factors’ in the title OR ‘success factors’ in the abstract OR ‘success factors’ in the thesaurus = 1,787,196 results.
   Combined search terms using AND = 524 results.
   Exclusion/inclusion filters applied: ‘peer reviewed’ = 57 results.
   Excluding biotechnology-oriented papers and duplicates = 41 results.

At the end of these seven procedures, we were left with 175 papers, where 49 papers were duplicates (i.e., identical papers returned in multiple searches). Excluding the duplicates, we had a total of 126 papers. We analyzed these papers’ abstracts and methodology sections, and additional exclusions were applied. We excluded papers on education, crowdfunding, legal procedures, governmental aids, governmental policy, university spin offs, and case studies as these did not fit with our inclusion criteria.

Theoretical papers were also excluded. This is a common exclusion procedure. “Theoretical work in such analyses is undertaken predominantly before and after the review, not during the review, and is concerned with developing the hypothesis and interpreting the findings” (Gough et al, 2012, p. 3).

It is relevant to mention that although these papers were excluded for our systematic review dataset, the majority of them were relevant for the construction of our objectives, hypotheses and understanding of the current literature available.

We were left with our focal set of papers, which consisted of empirical papers that had ‘VC backed companies’ success’ as their dependent variable. This allowed us to assess the different definitions of success used by academic authors, as well as the predictors of success identified in these studies. Our final sample was a total of 53 papers (see Appendix 4).

4. Data analysis: empirical papers

As mentioned before, our systematic review included a sample of 53 empirical papers. In Appendix 4 we have referenced each of these papers in order to facilitate transparency in this research’s outcomes.

4.1. Descriptive Statistics of Sample

As expected, a great deal of our sample was concentrated on data from the USA and Europe. Both add up to over 80% of all the data in our sample. Asia also had a significant amount of data, adding a little over 10%. African countries represented over 5% of our data. Oceania countries represented only 1,8%. The least represented continent and location in our focal sample was South America, with only one paper mentioning data from Chile, and its data wasn’t exclusively from South America, as it also gathered and analyzed data from North America.

Figure 3 - Location of the sample's data. Source: Created by the author based on our data. In this figure Russia was considered as an Asian Country. The US, although not a continent, was considered a separate category by itself due to its overwhelming significance within our sample.

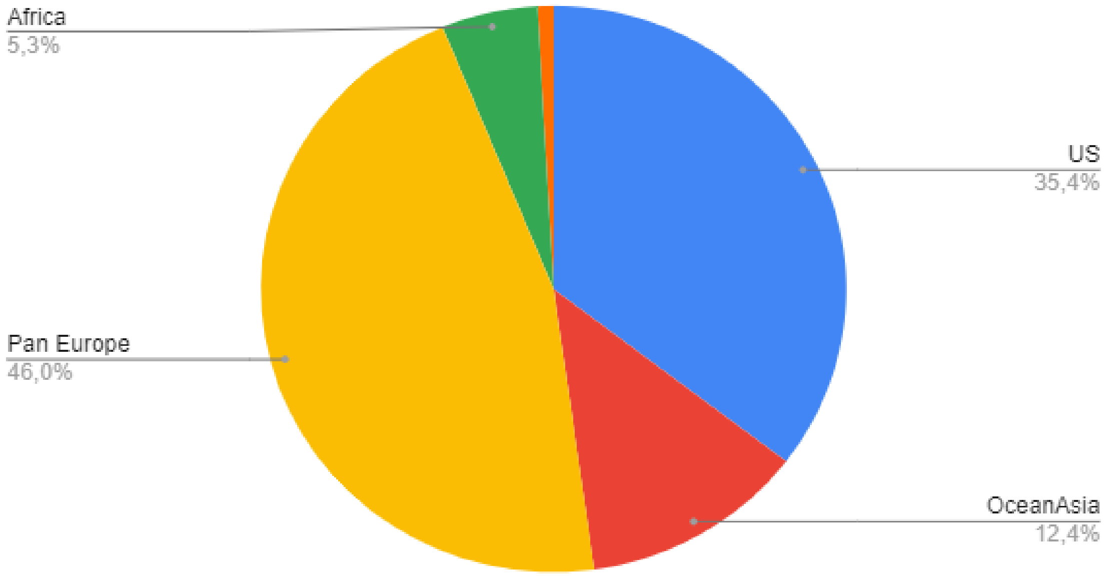


Figure 4 shows the origin of our sample's data based on their country. Some papers examined several countries from Europe simultaneously, that is why there is a category for the continent 'Europe'. The majority of these papers were concentrated on the UK and Germany, although not exclusively.

Figure 4 - Country of sample's data. Source: Created by the author based on our data.

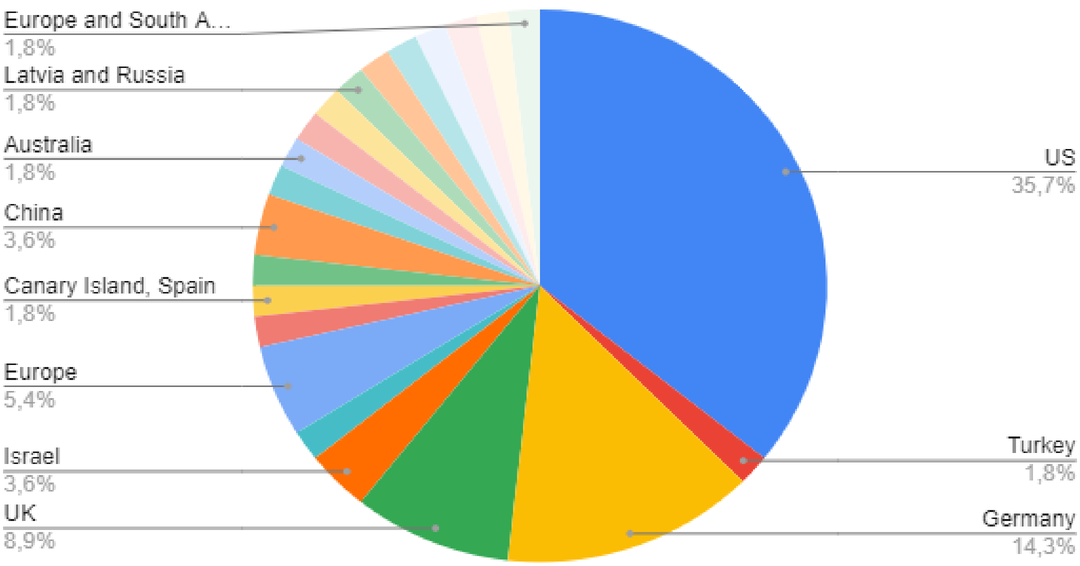


Figure 5 shows a histogram of the papers in which venture capital backed companies' success was examined, regardless of their methodology and approach. As can be observed, 2010 was the year with the highest number of published papers on this topic.

Figure 5 - Histogram of the papers - here we considered all papers that offered a definition of the success of venture capital-backed companies, regardless of their methodology. Created by the author based on our data, 2022.

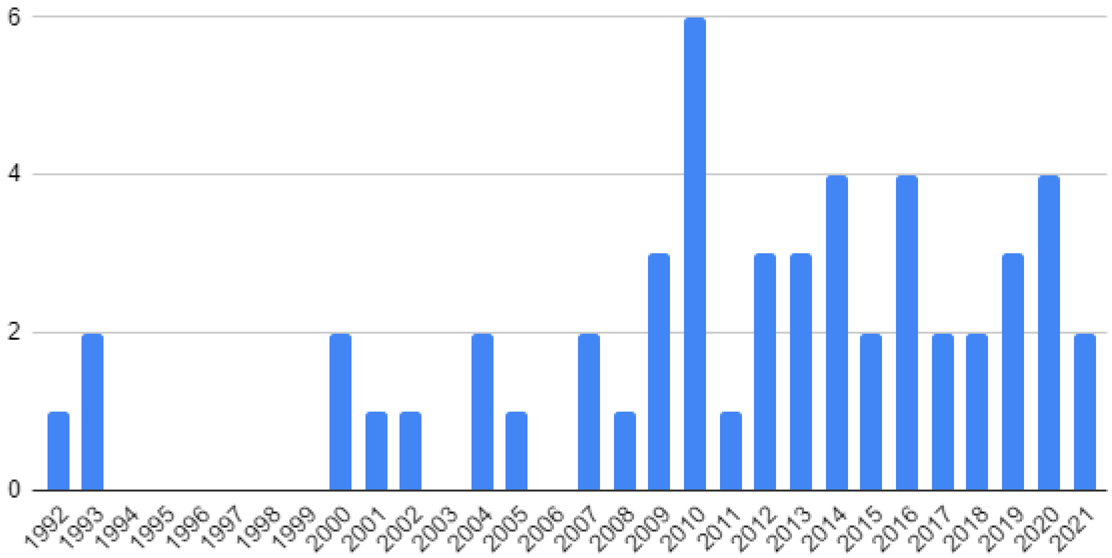
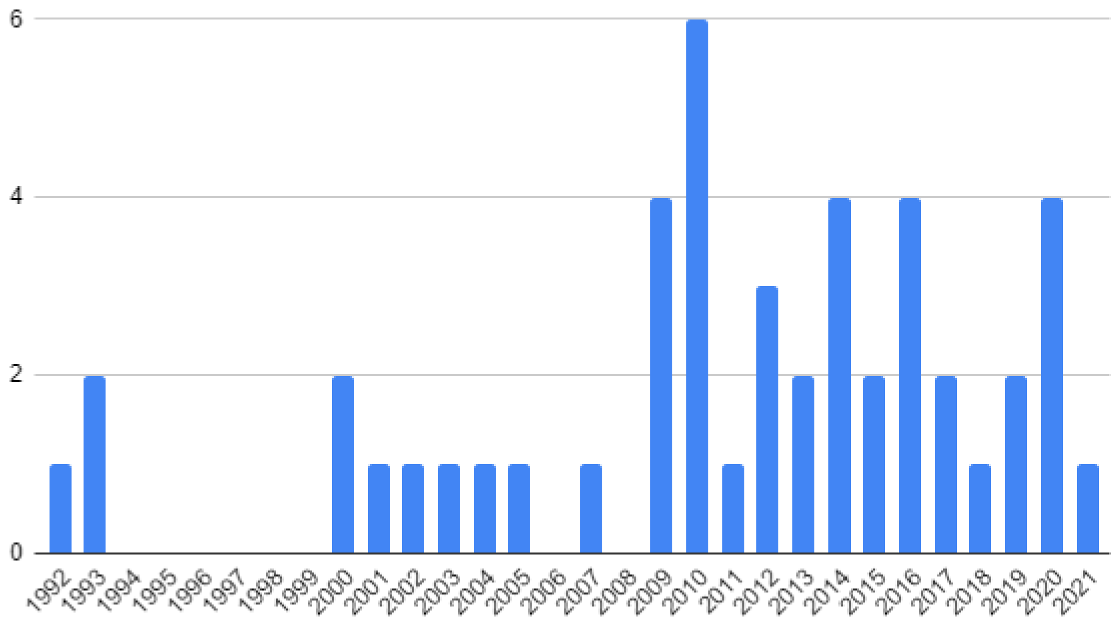


Figure 6 is also a histogram of the papers that examined and measured venture capital backed companies' success, but in this case, we only include the empirical studies.

An interesting observation about the histograms shown in both Figure 5 and Figure 6 is that in our paper's sample we had no data from 1994 to 1999. These are the main years of the dotcom bubble forming (also called the internet bubble), that later burst in 2000 leaving many with great skepticism about the future of Venture Capital.

Figure 6 - Histogram of published papers from 1992 to 2021 Here we considered only empirical papers that had success as their dependent variable. Source: Created by the author based on our data, 2022. Source: Created by the author based on our data, 2022.



After the burst, a great deal of interest arose as to how, and based on what, analysts were evaluating the venture capital backed companies. Boissin and Sentis (2014) explain that both regulators and the financial press have pointed out that analysts' research was tainted by conflicts of interest, and academic literature has revealed that analysts were biased towards providing favorable reports to the detriment of their objectivity and reputation. A need for clear and objective parameters to determine the value of young and venture capital companies was clearly required.

4.2. Quality of the journals

Another statistical information that we found relevant to disclose was about the quality of the journal in which each paper in our sample was published. We have gathered two main sources of information about journal quality: impact factor and its quartile, both based on the general ranking of 2020. As can be seen, papers which defined and measured success based on IPO tended to be published in high impact factor journals, with 100% of these articles appearing in quartile 1 journals. In contrast, papers that used self-developed scales to measure success tended to appear in lower ranking journals with only 40% appearing in top quartile journals.

Table 3 – Systematic review papers' dependent variable and the quality of the journal they were published in. Source: Created by the authors, 2021.

Dependent variable	IF mean	Highest (IF)	lowest (IF)	% of Q2, Q3, and Q4	% of Q1
Exit	1,5	5,06	0,29	33%	66%
Funding amount	2,11	5,37	0,27	50%	50%
Ipo	3,9	11,67	1,67	0%	100%
Other	1,68	11,04	0,42	27%	73%
Self-developed	1,165	2,32	0,18	60%	40%
Survivability	1,44	12,8	0,27	33%	66%

A full assessment of each paper's journal and their quality measurement is presented in appendix 3.

5. Results: Empirical Research and Their Definition of Success.

Regarding our first research question concerning how academics have defined and measured the success of Venture Capital backed companies in their empirical studies, we find that there is the lack of a common language in the academic literature and research about how we define and assess a venture capital backed company's success. We found that authors primarily adopted five different definitions in the extant literature. These five main definitions were: (1) success based on IPO; (2) success based on other VC exits; (3) success defined as survivability; (4) success measured as the total amount of funding capital raised; (5) success defined as the number of capital funding rounds. There was also a great deal of research that developed self-reported and self-developed scales in order to define a venture backed company's success. Finally, some papers analyzed (18,6% of them) adopted several other definitions, such as profits, firms' growth, sales growth, employment growth, growth of brand assets, etc.

Success based on IPO is commonly mentioned as the ideal approach, as it has a common ground with mainstream valuation, where the stock market is considered central in driving one's value. Although an ideal definition, most research studies are unable to access this information. As we have argued, Venture Capital is a market around new companies most of which are still far from going public. This has become worse in the last years, where companies are determined not to go public for as long as possible for strategic reasons (Fan & Yamada 2020; Reiff & Tykvová, 2021).

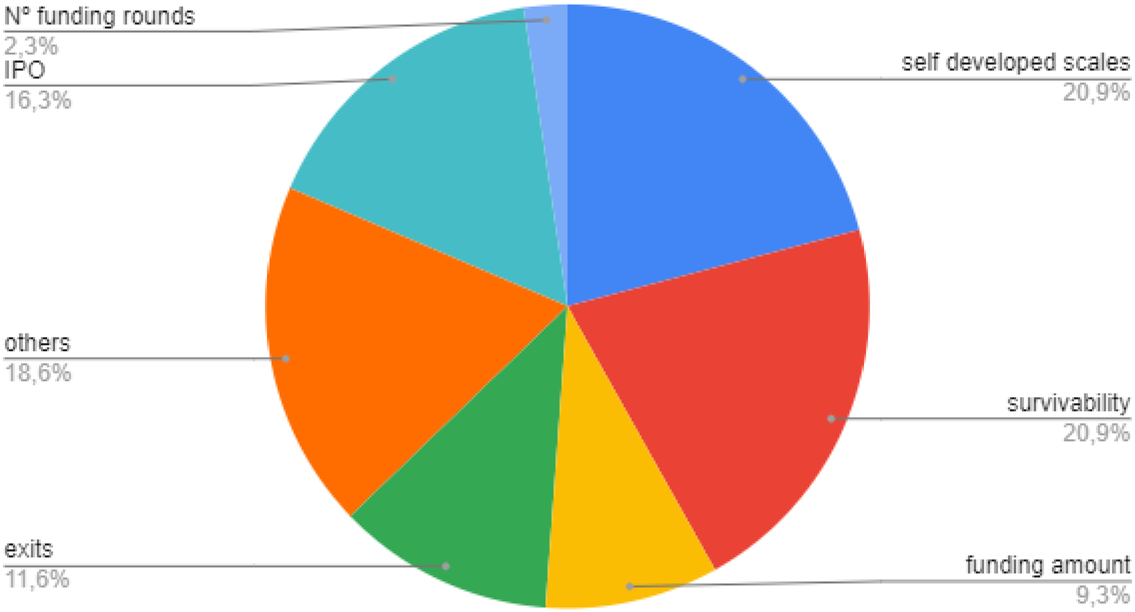
As shown in Figure 5, papers that define and measure success based on IPOs account for 16,3% of the total sample. Unfortunately, many countries and markets still don't have this type of data available as the venture market is still maturing in most parts of the world.

If we compare the papers that define success as having an IPO and their data, we can clearly see that this is possible only for mature markets such as the USA, Germany, and UK, which have had the venture capital market for many decades. One could even argue that Europe has had its market since the Age of Discovery where investors financed literal adventures with life threatening risks (Rind, 1981; Gompers, 1994).

This leads us to another subset of research that has considered any type of exit as an indicator of a venture backed company's success. If some markets still lack events, and therefore data on IPO, it is reasonable to consider that other events of liquidity, such as trade sales, secondary buy outs, private acquisition, or even a merger, when profitable can be considered an investment success. This is the approach considered by 11,6% of the research we analyzed.

This process of buy out and different type of liquidity can happen several times, some companies reach up to eight funding rounds before they go public (IPO). This explains why some researchers decided to assess a venture backed company's success by the number of these events – Nº of funding rounds. This group was a smaller one that accounted for 2,3% of the papers analyzed.

Figure 7 - Success definitions and their frequencies. Source: created by the authors, based on our sample's data.



Another cluster defines and measures success in terms of survivability, that is by measuring a company's longevity in not having closed down and avoided insolvency. This shows us how dynamic the market is, and how ideas come and go, companies rise and fall, and to survive a couple of years is in itself an accomplishment. Tough times! At least it's not a literal survival as in the 15th century, right?

Within the survivability cluster, we have several other issues: For example, how do we measure one's survival? Over a span of two years? Three years? In some years, do high potential companies just fail for macroeconomic reasons? And with that in mind, should we start counting from a company's founding date or pinpoint a common year for all of them? These questions are exactly what academics face and try to resolve in the best way they can.

Bates and Bradford (1992) take as successful the companies that have managed to still be operating in late 1986, regardless of their founding year. Brau, Brown, and Osteryoung (2004) established a time lapse of three years for a business's success. Others have measured survival as years that count not from the founding date, but the ones that follow a certain funding event. Kerr, Lerner, and Schoar (2014), for instance, measured survival as a minimum of four years after the potential funding event with a VC angel group.

Survivability is present even in research that has IPO data. Abdou and Varela (2009) for instance proposed that a public offering per se was not enough, the company still had to manage to survive after its IPO.

Even some self-developed scales and self-reported success measures consider survivability as a game changer. Baluku, Kikooma, and Kibanja (2016) developed a success questionnaire using a Likert scale where the instrument comprised 16 items measuring four factors of success: financial rewards, survival time, owner’s satisfaction and generated employment.

Apart from making the evolutionists proud, this also gives us the knowledge that one way or the other survivability is considered by many as a natural manifestation of one’s success. Maybe Darwin’s evolution theory can indeed explain it all, or at least explain the dynamics of Venture Business.

Self-reported scales have certainly been used frequently as a way to overcome all of this. Apart from all the major issues associated with self-reported data, such as interview mood bias, overwhelming hopes from entrepreneurs, social desirability bias, and so on, another issue we face is that there still isn’t a well-established and validated questionnaire or single agreed upon measure of success.

In Table 4 we present some information on how researchers have described the main dimensions that they based their scales on.

Table 4 - Self-reported scales. Source: created by the authors, based on our sample’s data, 2021.

Reference	**Descriptions of self-reported scales**
West and Noel (2009)	Success was measured by subjective assessment based on three questions: their percentage of ideal performance being achieved, and two questions concerning their overall performance compared to other similar companies.
Baluku, Kikooma, Kibanja (2016)	The entrepreneurial success questionnaire was designed using a Likert scale (1 disagree strongly to 5 agree strongly). The instrument comprised 16 items measuring four factors of success: financial rewards, survival time, owner’s satisfaction and generated employment. Sample items include: the financial success of my business in

	the past year has been impressive, and I am satisfied with the rate at which my business is growing.
Tinkler et al., (2015)	To measure evaluations about the venture's potential for success, they asked participants to rate the company on a 6- point scale. Example questions included "how unique is the company's product?", "how interested would you be in buying the company's product?", and "how likely would you be to schedule a meeting with the company's founder to learn more about the venture?". They constructed a composite "optimism for the venture" scale with combined question sets by creating scenarios of business opportunities and asking participants which ones they are more likely to invest in.
Kessler (2007).	Success was measured through a survey. The qualification of a case as 'successful' was based on the fulfilment of a combination of four (partly objective, partly subjective) criteria: 1. full-time start-up; 2. no negative change in the number of employees in the period between business establishment and the survey 3. subjective assessment of the entrepreneur's track record to date as 'successful' or 'very successful'; 4. subjective assessment of future business development as 'constant' or 'expansive'.
Harrison, Mason, Smith, (2015)	verbal protocol analysis, a methodology for examining decision-making in real time, with three groups of business angels with differing levels of investment experience, and with follow-up debriefing interviews with these angels.
Sapienza and Amason (1993).	Venture capitalist filled out questionnaires assessing both high and low performing/successful ventures.
Weber, Weber (2010).	Pre-tested self-reported questionnaire. Organizational performance was measured for the Portfolio Company (PC) in terms of sales, return on investment, and market share. The Portfolio Companies (PCs) that did not have this information were not included in the research. The information was assessed by partially standardized open, guideline-supported interviews. They looked at the absolute amounts of these measures and, when applicable, the growth rates in comparison to the previous year and to the business plan. PCs that performed badly with no improvement and who were potentially close to insolvency were scaled as 1. PCs with high sales, big market share, and even a high return were given a 5.
Streletzki and Schulte (2013)	They gathered information from the first-round business plans of relevant companies that got funded and exited by German VCFs. Then, they asked the VCFs to state their exit performance for each of those companies in order to obtain the corresponding success variable.

Kuckertz and Kohtamaki (2010)	Interviews and surveys were conducted where success was determined with questions based on exploitation, innovation performance and venture performance

It is also relevant to state that the papers that used self-developed scales to assess a company's success showed the worst results as to their journal quality. Their impact factor was the lowest, with 1,165 as its mean. Moreover, 60% of them were in journals Q2, Q3, and Q4. This fact could be related to the fact that there still is not a validated measurement scale to define a venture capital backed company's success.

As mentioned earlier, a full assessment of each paper's journal and their quality measurements can be found in appendix 3.

5.1. Independent Variables

In our research we have found that studies have examined a wide variety of predictor/independent variables that may explain a venture's success. Among the 53 papers analyzed we found over 20 different independent variables that were used, thus, making it difficult to compare their results among each other. To overcome this issue, we made use of the main categorization developed by Ferrati and Muffatto (2021) in their review, in order to cluster the many variables that were used to predict a venture's success.

Ferrati and Muffatto (2021) argue that venture capitalists usually apply a set of criteria to evaluate an entrepreneurial project's prospects. However, since each investor considers different criteria, researchers also end up analyzing a variety of divergent aspects. With this in mind, they carried out a systematic review to identify and classify all the criteria considered by previous researchers. The following classification was presented by Ferrati and Muffatto (2021) as a result of their research. In table 5 it is also possible to see the frequency with which the papers they analyzed made use of each variable.

Table 5 - Thematic clusters of the assessment criteria applied by equity investors. Source: Ferrati & Muffatto (2021).

Venture specific factors (76.0%)	Characteristics of the entrepreneur and/or the management team (34.1%)	Entrepreneur personality
		Entrepreneur experience and background
		Entrepreneur expertise and skills
		Entrepreneur motivations
		Entrepreneur commitment
		Entrepreneur reputation
		Entrepreneur demographics
		Entrepreneur / investor fit
		Team
		Venture network and affiliations
	Characteristics of the product / service (13.0%)	Product / service development
		Product / service innovation
		Product / service advantages
		Products / services portfolio
		Product / service economics
		Operations
	Characteristics of the market (11.1%)	Market and customers
		Competition
		Market access and development
	Venture financials (6.7%)	Venture financial indicators
		Venture access to finance
		Costs
	Business model (1.0%)	Business model and strategy
	Proposal (5.3%)	Quality of the proposal
	Venture's other factors (4.8%)	Venture's other specific factors
Investor specific factors (14.9%)	Investors related factors (12.0%)	Investor screening focus
		Expected return on investment
		Investment synergies
		Contractual terms
	Investor's other factors (2.9%)	Investor's other specific factors
	Macroeconomic factors (3.4%)	International factors

Environmental factors (3.4%)		National and ecosystem factors
Risk assessment factors (5.8%)	Risk factors (5.8%)	Market risks
		Agency risks
		Country and Ecosystem risks

It is interesting to see the link between Ferrati and Muffatto's (2021) classification and fundamental theories that explain VC behavior. Concerning venture specific factors, such as the characteristics of the entrepreneur – experience, education, expertise, reputation, etc., these can be explained both by Knowledge and Learning Theory, as well as by Signal Theory. On the other hand, both venture specific and 'team' factors, as well as investor specific factors can be explained by Network theory. Characteristics of the Products and Services find their basis in Finance of Innovation Theory. Environmental factors, such as ecosystems, have a direct link to Institutional Theory. And, among all the variables that academic researchers have studied in order to better understand what drives VC investments, we can rely on Agency Theory to explain the reasoning behind this process.

For a better summarization of Ferrati and Muffatto's (2021) findings, we have slightly condensed their categorization in the following table:

Table 6 – Condensed thematic clusters of the assessment criteria applied by equity investors from Ferrati & Muffatto (2021). Source: Created by the authors based on Ferrati & Muffatto (2021).

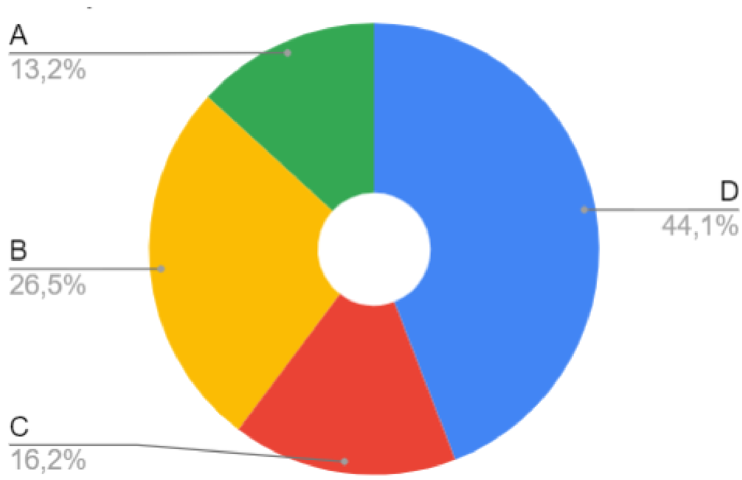
Ref	Category	Variables (Ferrati & Muffatto, 2021)	Percentage (Ferrati & Muffatto, 2021)
A	External factors	Risk factors and Macroeconomic factors	13.2%
B	Investor's factors	Investors related factors and Investor's other factors	14.9%
C	Characteristics of the product / service, financial, business model and proposal	Characteristics of the product / service, Characteristics of the Market, Venture financials, Business model, Proposal, and Venture's other factors.	41.9%

D	Characteristics of the entrepreneur and/or the management team	Characteristics of the entrepreneur and/or the management team	34.1%

Using our concise version of Ferrati and Muffatto's (2021) classification, our data shows a very similar frequency of the independent variables used as theirs.

The following Figure 8 shows our findings.

Figure 8 - Frequency of independent variables used by researchers. Source: Created by the authors based on data, 2021.



Caption: A: external factors; B: investors' factors; C: characteristics of the product / service, financial, business model and proposal; D: characteristics of the entrepreneur and/or the management team.

Although Ferrati and Muffatto's (2021) main concern was regarding the variables used by venture capitalist in their decision-making process, and our research focuses on the variables that can predict a venture capital backed company's success, both of our findings show that there is a high prevalence of the use of both entrepreneurial and business characteristics, as well as a lower frequency of researchers using external and investors' factors.

5.1.1. Characteristics of the entrepreneur and/or the management team

This category was the one that presented the widest variety of variables. They were founder’s age, founder’s expertise, founder’s qualification, founder’s experience, founder’s management experience, founder’s race, founder’s network, founder’s personality traits, founder’s gender, founder’s reputation, whether or not the founder has had venture company experience, number of founders, founder’s level of education, and whether or not the founder has a family member who owns a business.

We observed some divergence in the findings regarding how an entrepreneur and/or the management team influence a VC-backed company’s success, especially when self-reported and self-developed scales were used to measure success. Another situation in which there is a clear divergence in results concerns studies that define success as survivability. There are many problems that arise with this definition of success. One of them is due to the economic timing in which a firm’s survivability is considered (for macroeconomic reasons). An additional issue relates to the length in years, or the period of time considered in particular studies. And the main problem arises when we integrate both issues. That is: should we consider the survivability of a company from the moment it was founded, and in this case accept the macroeconomic differences between firms? Or should we establish a period of years common to all companies, and in this case accept that some companies have already survived longer than others? These issues may explain why researchers have found divergence in their results.

Table 7 - Findings for Category D. Source: Created by the authors based on data, 2021. Note: Nonsig denotes non-significant, Freq denotes frequency.

Category D - characteristics of the entrepreneur and/or the management team							
	Findings			Definition of success			
Variables	Pos	Neg	Nonsig	Positive	Negative	Nonsignificant	Freq
age	50%	0	50%	Self-developed scale	-	Self-developed scale	2
expertise/ qualification	85%	7%	7%	Funding amount, self-developed scale, exists, survivability, firm's growth, internal rate return,	number of funding rounds	self-developed scale	14
experience	70%	10%	20%	funding amount, survivability, exits, growth, self-reported scale, number of funding rounds	survivability, number of funding rounds	self-developed scale, self-reported success, sales growth in a period of 3 years	20
network	89%	11%	0	funding amount, number of funding rounds, exits, IPO, survivability, self-developed scale,	survivability	-	9
personality traits	75%	0	25%	Self-developed scale, sales growth	-	Self-developed scale	4
gender (male)	75%	25%	0	Self-developed, sales growth in a period of 3 years	self-developed	-	4
reputation	100%	0	0	Survivability post IPO, survivability	-	-	2
prior venture capital	100%	0	0	number of funding rounds	-	-	1
number of founders	100%	0	0	funding amount	-	-	1

level of education	80%	0	20%	exists, IPO, survivability, funding amount	-	sales growth in a period of 3 years	5
family member owned a business	100%	0	0	survivability	-	-	1
management experience	0%	33%%	66%%	-	survivability,	Stock price performance, sales growth in a period of 3 years	3
race (minorities)	0	100%	0	-	IPO, survivability	-	2

In Table 7 we present our systematic review's findings regarding the papers that made use of any independent variable in category D to explain a venture capital backed company's success. The most frequently used variable was the founder's experience, which appeared in twenty of the fifty-three papers analyzed. Among these twenty papers, the majority of them (70%) found a positive correlation between time experience and a venture's success. Two papers found a negative correlation between this variable and its success, and as shown, their definition of success was survivability in one case and number of funding rounds in the other. It is interesting to note that there were papers that also defined success with survivability measures and found a positive association. This may be due to the issues with 'survivability' measurements, cited above. Another interesting observation is that within the four papers (that is, 20%) that found a non-significant relationship between time experience and a venture's success, three of them made use of self-developed or self-reported scales to assess success. This suggests that perhaps these scales are biased or ineffective in assessing success. Such findings highlight the need for a common and validated scale in this field and also underline the limitations of using subjective self-developed/self-reported scales rather than objective measures of success.

5.1.2. Characteristics of the product/service, financial, business model and proposal

Table 8 - Findings for Category C. Source: Created by the authors based on data, 2021. Note: Nonsig denotes non-significant

Category C - Characteristics of the product / service, financial, business model and proposal							
	Findings			Definition of success			
Variables	Pos	Neg	Nonsig	Positive	Negative	Nonsig	frequency
Market	67%%	0%	33%%	Self-developed scale	-	Funding amount	3
Market (being unique in a market)	100%%	0%	0%	Survivability	-	-	1
Market (being attractive)	100%	0%	0%	Self-developed scale	-	-	1
Market (strategy on profits)	100%	0%	0%	Self-developed scale	-	-	1
High Reward Options	100%	0	0%	Funding amount	-	-	1
Resources	80%	0%	20%	Survivability, Funding amount, self-developed	-	Self-developed scale	5
Business Model	50%	50%	0%	Profits	Funding amount	-	1

5.1.3. Investors' factors

Table 9 - Findings for Category B. Source: Created by the authors based on data, 2021.

Category B – Investor's factors							
	Findings			Definition of success			
Variables	Positive	Negative	Nonsignificant	Positive	Negative	Nonsignificant	frequency
VC's type	73%	-%	27%%	survivability, exits, IPO, others	-	self-developed scale, survivability	11
VC's experience	80%	10%	10%	Funding amount, survivability, IPO, self-developed scale	Self-developed scale	Self-developed scale	10
Human Resource (HR) vice president	0%	0%	100%	-	-	VC-backed firms value (in terms of stock price performance)	1

Regarding the Venture Capitalists' factors that are associated with a firm's success, most findings point to the same result, regardless of the approach as to how success was defined. Most of them suggest that both an experienced investor and an investor that is specialized in a given investment stage (such as seed money, early-stage ventures, or late-stage ones) are positively associated with a venture's success. It is relevant to state that we cannot necessarily conclude a causal relationship exists between these variables, merely a correlation.

5.1.4. External Factors

Table 10 - Findings for Category A Source: Created by the authors based on data, 2021.

Category A – External factors							
	Findings			Definition of success			
Variables	Positive	Negative	Nonsignificant	Positive	Negative	Nonsignificant	frequency
Country/ location (high VC)	86%	-	14%	IPO, exits, self-developed, others	-	Funding amount	7
analyst coverage	100%	0%	0%	amount raised on IPO	-	-	1
government sponsorship	100%	0%	0%	others	-	-	1

Notice that, as indicated in table 10, different approaches to success's definition largely had the same outcome here, showing a positive correlation between the number of venture capitalists in a country or location and success. On the other hand, the one study that defined success as the average funding amount raised found a non-significant association.

5.2. Predictors of success and their issues.

Regarding our second research question: Do different definitions of success lead to conflicting results? That is, how do the predictors of success identified in empirical research differ depending on the definitions/operationalizations of success adopted by the studies' authors; we have summarized all of the associations found between the predictors and the explanatory variables in table 11 that follows.

Table 11 - Summary of all associations found. Source: Created by the authors based on data, 2021.

Explanatory / Predictors	IPO	Exits	FA	Surv	Prof	SaG	FirG	IRR	NFR	Self D	Oth.
Country/location(high VC)	+	+	Ns							+	+
analyst coverage	+										
government sponsorship											+
VC's type	+	+		+ / -						-	+
VC's experience	+		+	+						+ / - / ns	
Human Resource (HR) vice president											ns
Market			ns							+	
Market (unique)				+							
Market (attractive)										+	
Market (stratg profits)										+	
High Reward Options			+								
Resources			+	+						+ / ns	
Business Model			-		+						
Age										+ / -	
expertise/qualification		+	+	+			+	+	-	+ / ns	
experience		+	+	+		-	+		+ / ns	+ / -	
network	+	+	+	+ / ns					+ / ns	+	
personality traits						+				+ / -	
gender (male)						+				+ / ns	
reputation	+			+							
prior venture capital									+		
number of founders			+								
level of education	+	+	+	+		ns					
family member owned a business				+							
management experience				-		ns					ns
Ethnicity (minorities)	**-**			-							

Where: FA is funding amount; Surv is survivability; Prof is profit growth; SlG is Sales growth in a period of three years; FirG is firm's growth; IRR is internal return rate; NFR is number of funding rounds; Self D is self-developed or reported scales; and Oth stands for others (profits after IPO, *returns being higher than Nadasq, employee growth, number of employees, patents, web traffic, etc). Stratg is strategic*

Here we face yet another concern with how success is defined and measured in empirical studies. Specifically, it can be noted that some definitions of success may be regarded as the opposite of others. For example, average funding amount (funding amount divided by the lifetime of the venture backed company) can be perceived as the opposite of survivability. The first one implies downgrading its success score as it adds years of survival in the market. And for this matter, the results should also show this discrepancy.

Another example of a discrepancy due to opposite definitions seems to be regarding exits and survivability, especially when we consider IPO exits. A company that has survived several years but has not yet passed through its initial public offering may be considered both successful and unsuccessful depending on one's approach. This is just another marker of how hard it is to measure success in an area where definitions and operationalizations are not yet widely established or agreed upon.

Although this deduction may seem reasonable, the wide variety of approaches, data, and variables do not clearly point out this issue. We have observed that as researchers have embraced a wide variety of different criterion variables (i.e., different definitions of success) and have often focused on different explanatory/predictor variables, there is insufficient data to make comparisons. In other words, we can only develop a comprehensive understanding of different predictors of success when researchers have chosen to use the same predictors and criterion variables (i.e., definitions of success) in their analysis.

For instance, regarding 'country/location (high VC)' we can observe that having a high number of venture capitalists in a location is positively correlated with IPO and other exits. At the same time, it has a negative association with average funding amount. While this makes a case for our hypothesis (that predictors of success will vary depending on how success is defined), the fact that there is no further information on other approaches still leaves us wondering why this could be happening. Perhaps companies near clusters of a developed VC market, with high liquidity and efficiency, are indeed more likely to reach an exit, and the fact that funding amount is negatively correlated with this is just a counter effect of their extended survivability. Alternatively, we could argue that Venture Capitalists are more inclined to invest greater amounts in companies that are distant from the highly developed clusters. The fact is that all these assumptions and interpretations are speculative. We would have to go deeper into the data and its specificities (and likely collect new empirical data) in order to better understand this process.

The self-developed scales are the ones that present the most divergent outcomes. The explanatory variables are frequently shown to have different outcomes. Take a 'VC's experience' for example. As shown in table 11, this is at the same time presented as having a positive, negative and non-significant effect on success (in different empirical studies using self-developed scales). Such findings reinforce the need for a single, reliable and validated scale.

6. Discussion

In order to assess the different definitions of success in the VC landscape, as well as the independent variables that aim to explain them, a systematic review of 53 papers was conducted. This review has drawn attention to three relevant points:

- The majority of empirical research papers have concentrated on data from the USA and Europe, adding up to over 80% of the published papers analyzed. Since the VC market is expanding to cover more countries around the world, there is a need to broaden academic research in order to understand VC markets in other contexts.

- The academic literature and research field lacks a common understanding of how to define and assess a venture capital backed company's success, which leads to confusion about what we mean when we talk about success and inconsistencies in our understanding of the predictors of VC outcomes.

- Self-developed scales are often used to assess a VC backed company's success. Unfortunately, the lack of a pre-validated scale for such a purpose leads to confusing and contradictory results among these studies. This sheds light on the need for a valid scale that is capable of measuring VC backed companies' success with different methodology, such as through surveys and interviews.

CHAPTER 3

STUDY 2 - A Study on the Likelihood of Venture Capital Backed Companies' Success in Brazil

1. Introduction

Venture Capital (VC) is a rising market that enables cutting edge technological development across multiple industries. In the last couple of decades, it has extended beyond the boundaries of its origins (in areas such as the USA, and Germany) and it has spread throughout the world. Brazil is one of these countries that has had a rising role within the VC market's development.

The VC investment market is characterized by high risk and high returns, which increases the need for rational decision-making processes. This issue has led academic researchers to develop data-driven models that lead to insights into the intrinsic associations between the venture's model, composition, products, etc., and its success.

In this study we address the same issue with CrunchBase Brazilian data to explore data-driven models that estimate the worth of VC backed companies in Brazil in the moment of their foundation, considering especially non-financial features regarding the ventures' entrepreneurs. This research assesses the intrinsic aspects of the private companies as predictors of their overall success, such as their sector, founders' expertise and team composition. Differently from typical valuation models, as the worth of a startup is not well defined due to a lack of financials, we use a few success metrics instead. Here, success is defined in five different ways, giving birth to five different models.

It is of great importance to examine VC backed companies in a Brazilian context. Specifically, the previous chapter showed that we have a rich literature on VC backed companies and the factors that predict their success. However, there is still very little empirical research focusing on a Brazilian context. Indeed, the systematic review revealed only one study that focused on a South American country (Chile) and none that focused on Brazil. Therefore, this study complements and builds on the previous chapter, by providing a more fine-grained empirical analysis of VC backed companies' success in the Brazilian context.

2. Literature Review

The use of non-financial data to try to predict a VC backed company's success is not a novelty to the present study, but an approach that has been observed in recent VC research development. However, there is not a unified framework to define and predict the success of VC backed companies in the literature. The use of a wide variety of success definitions, approaches and (non-financial) independent variables is a common feature of this literature.

In Table 12 we show the independent variables that have been previously tested in academic research, and the relationships that they were found to have with a VC backed company's success.

The variable 'Foreigner', which denotes whether or not the founder is from Brazil, and 'Foreign Institution', which denotes whether the founder had their undergraduate education inside or outside of Brazil are both novel variables. That is, to the best of our knowledge these variables have not been tested in past research. Nevertheless, while mining the data we developed the feeling that they could have a direct association with a venture's success.

Table 12 - Independent variables found in previous studies to predict VC backed companies' success.

Variables	Description		Expected Relationship	Authors
Independent	Founder's Features	Number of founders	+	*West & Terry Noel (2009); Klein, Stuckenborg, & Leker (2020);*
		Gender - male	+	*Baluku, Kikooma, & Kibanja (2016)*
		Age	+/-	*Kessler (2007)*
		Previous Venture	+	*Walske & Zacharakis (2009)*
		Prior Experience	+	*Walske & Zacharakis (2009); Harrison, Mason, & Smith (2015);*
		Undergraduate	+/-	*Bates & Bradford (1992); Klein, Stuckenborg & Leker (2020)*
		Expertise	+/-	*Tinkler et al. (2015)*
		Foreigner	+	*Identified by the authors.*
		Foreign Institution	+	*Identified by the authors.*

Bates and Bradford's (1992) work is one of the earliest and most pioneering papers that addresses non-financial factors that affect a venture's success. Using an empirical approach involving over fourteen thousand firms, they found that attractive human capital traits at business entry for entrepreneurs (including high educational attainment, owners who lie in the middle of the age distribution, and a family business background) are some of the main characteristics that provide higher likelihood of survival in the market.

Gompers, Mukharlyamov, and Xuan (2016) argue that individuals tend to associate, interact, and bond with others who possess similar characteristics and backgrounds. However, the attraction to each other based on affinity that venture capitalists exhibit is costly. Investment teams that exhibit a high degree of similarity between members in characteristics not related to ability are less likely to succeed, according to this research.

Smart, Payne, and Yuzaki (2000) conduct a survey and argue that soft skills are valued more highly than quantitative skills (e.g., accounting or finance), and overall intelligence is cited as very important for success. Abdou and Varela (2009), find that reputation and experience of VCs are major factors in extending the lifespan in the Venture Capital market.

Social networking also helps fill the financial information gaps. As Moore (2000, p. 61) explains:

> “In the corporate environment, one finds experts, mentors, and a range of support facilities. Once in business for yourself, however, gaps in knowledge, training, or information, not recognized in the supportive organizational climate, can surface quickly. Ties to others become critical. That is why the path of business success winds through networks. Entrepreneurs who develop the skills to cross boundaries, make connections, and link resources tend to be the most successful” (Moore, 2000, p. 61).

Social networks are often found to be positively correlated to a company’s success (Dashti & Schwartz, 2018; Echols & Tsai, 2005; West & Noel, 2009; Bellavitis, Filatotchev, & Kamuriwo, 2014). On the other hand, while analyzing over a hundred FinTechs in Germany, Klein, Stuckenborg, and Leker (2020) found a negative association between a network and its attractiveness.

3. Hypotheses

In this empirical study, we test five different hypotheses that link a range of non-financial indicators/predictors (more specifically, founders’ characteristics) to five different metrics of success, as follows:

Hypothesis I: VC **Funding Amount** can be partially determined by the company’s team composition, founding team size, management team size, CEO’s education and expertise, team experience and by the VC’s size, type, age and country of origin.

Hypothesis II: **Survivability** of privately held companies, based on time, can be partially determined by the company's team composition, founding team size, management team size, CEO's education and expertise, team experience and by the VC's size, type, age and country of origin.

Hypothesis III: **Revenue** of VC backed companies can be partially determined by the company's team composition, founding team size, management team size, CEO's education and expertise, team experience and by the VC's size, type, age and country of origin.

Hypothesis IV: **Number of funding rounds** of VC backed companies can be partially determined by the company's team composition, founding team size, management team size, CEO's education and expertise, team experience and by the VC's size, type, age and country of origin.

Hypothesis V: **CrunchBase Rank** of VC backed companies can be partially determined by the company's team composition, founding team size, management team size, CEO's education and expertise, team experience and by the VC's size, type, age and country of origin.

4. Methods

4.1. Context and procedures

The data that was worked with in this research was Brazilian data on Brazilian Venture Capital backed companies. All of the data was obtained from the CrunchBase platform in 2020. CrunchBase is a platform that mines public articles from the internet to create its data set. There was a total of 905 Brazilian companies included in the first simple search at CrunchBase. This number was drastically reduced when we excluded misplaced foreign companies, double entries of the same company, and those that did not achieve the data requirements - that is, those that did not include both companies' and founders' information.

It is relevant to state that although it is an innovative and rich data platform, CrunchBase has been used recently in many empirical academic works (Nathan, Kemeny & Almeer, 2017; Ferrati & Muffatto; 2020) As we have discussed, as opposed to publicly traded companies, in the Venture Capital market there is no obligation to disclose any information. Researchers face a constant issue with the lack of information to work with. CrunchBase uses voluntarily public information available on the world wide web to create a wide database of all the venture around the world. It is constantly improving its algorithms to increase data quality and reduce errors. Nevertheless, in this research we found a great deal of missing data and some inaccuracies in the information provided.

In order to validate the remaining data, a manual audit process was conducted, focusing on each and every company, crosschecking the information provided by CrunchBase with information online and on Linkedin. Although this double-checking effort took place, CrunchBase was essential in providing an initial list of companies to get the work started.

Excluding non-usable inputs from our data, we ended up with a total of 309 founders that represent 249 Brazilian Venture Capital backed companies (see table 14). The number of founders is higher than the number of companies as each company may have been founded by more than one entrepreneur. Although that is the case, we found that the majority of companies in Brazil were founded by a single person. The total number of founders and venture capital backed companies is displayed in the table that follows.

Table 13 - Number of founders and venture capital backed companies. Source: Created by the authors based on data of 2020.

Number of founders	**Quantity of VC backed companies**	**Number of founders**
1	201	201
2	24	48
3	10	30
4	3	12
6	1	6
12	1	12
Total:	**249**	**309**

Based on our data sample, the majority of Venture Capital backed companies in Brazil are founded by a single person, with 80% of all companies in the sample having one founder.

As can be seen in Table 15, most of the companies were founded in the last few years. This can be due to the fact that Venture Capital has been catching up in Brazil in recent years. For that matter, there was a lack of Venture Capital activity in the country in the years before 2000. It should also be mentioned that the data was gathered in March of 2020. Thus, even though the category of '2015-2020' has the highest number of companies, this is still an underestimate of their total number.

Table 14 - Year of VC backed company foundation. Source: Created by the author based on data up until 2020.

Years	Ventures comp. founded
2000-2004	9
2005-2009	24
2010-2014	123
2015-2020	153
Total	**309**

Table 16 (in section 6.1 below) presents a summary of the descriptive statistics on the companies' characteristics, that is the age of the founders in the moment they founded the company analyzed, the year the company was founded, and the prior experience of the founders.

4.2. Measures

Here we describe how each variable was measured. Table 15 below contains a summary of all the models' variables, their description, measurement and the expected relationships between the independent variables and the dependent variables. Additionally, this table presents a short summary of other authors that have examined each of the listed variables.

Table 15 - Variables' descriptions. Created by the authors. (2020 - 2022).

<table>
<tr><th>Variables</th><th colspan="2">Description</th><th>Proxy</th><th>Code</th><th>Expected Relation-ship</th><th>Authors</th></tr>
<tr><td rowspan="5">Dependent</td><td colspan="2">VC Funding Amount/ Year</td><td>Sum of dollars invested by a VC per year</td><td>TF</td><td>+</td><td rowspan="5">Bates & Bradford, 1992; Engel, 2004; Gerpott & Niegel, 2002; Walske & Zacharakis, 2009; Kerr, Lerner & Josh, 2014; Prohorovs, Bistrova & Ten, 2018; Klein, Stuckenborg, & Leker, 2020.</td></tr>
<tr><td colspan="2">CB Rank</td><td>Crunch Base's Ranking</td><td>CB</td><td>+</td></tr>
<tr><td colspan="2">Opened status</td><td>Opened or Closed Status</td><td>OC</td><td>+</td></tr>
<tr><td colspan="2">Funding Rounds</td><td>Number of funding rounds</td><td>FR</td><td>+</td></tr>
<tr><td colspan="2">Revenue</td><td>Elevated revenue per year</td><td>ER</td><td>+</td></tr>
<tr><td rowspan="9">Independent</td><td rowspan="9">Founder's Features</td><td>Size</td><td>Number of founders</td><td>S</td><td>+</td><td rowspan="9">Sapienza & Amason, 1993; Schefczyk, 2001; Barth, Beaver, & Landsman, 2001; Gerpott, & Niegel, 2002; Kessler, 2007; Walske & Zacharakis, 2009; West & Noel, 2009; Streletzki & Schulte, 2013; Tinkler et al., 2015; Gompers, Mukharlyamov, & Xuan, 2016; Rasmussen, Ladegård, & Korhonen-Sande, 2018; Prohorovs, Bistrova & Ten, 2018; Klein, Stuckenborg, & Leker, 2020.</td></tr>
<tr><td>Gender</td><td>Female or male</td><td>G</td><td></td></tr>
<tr><td>Age</td><td>Age of the founders on the date of founding the company</td><td>A</td><td>+/-</td></tr>
<tr><td>Previous Venture</td><td>If the founder has had a previous venture experience</td><td>PV</td><td>+</td></tr>
<tr><td>Prior Experience</td><td>Years of experience working before the venture was founded</td><td>Ex</td><td>+</td></tr>
<tr><td>Undergraduate</td><td>Founders' undergraduate area.</td><td>Und</td><td>+/-</td></tr>
<tr><td>Expertise</td><td>Founders' expertise level</td><td>E</td><td>+/-</td></tr>
<tr><td>Foreigner</td><td>Flag for foreigner founders</td><td>F</td><td>+</td></tr>
<tr><td>Foreign Institution</td><td>Flag for foreigner education of founders</td><td>FI</td><td>+</td></tr>
</table>

4.2.1. Independent Variables

Gender is a binary variable where 1 stands for male, and 0 for female.

Size relates to the number of founders.

The **age of founders**, as argued before in the literature, is seen as a variable that may be related to the likelihood of a venture's success. It is relevant to note that the age of the founder we aim to measure is at the moment they founded their company, not today. As we discovered after using the LinkedIn platform, there is no direct access to founders' age provided by LinkedIn. Nevertheless, this information can be easily estimated from other given information – such as the year the founder finished high school or the year the founder finished college. In this sense, our age variable is better called 'likely age', as it may contain some (minor) estimation errors. Despite this, we argue that it is still a valuable variable and is a well-constructed estimation and proxy of the founder's real age.

Our procedure to assess founders' age was as follows:

- Likely age = year the company was founded – probable birth year.
- Probable birth year = Year they finished high school – 18; or,
- Probable birth year = Year they graduated – 23.

Previous Venture is a binary variable, where 1 indicates the founder has had a previous experience of founding a venture capital backed company before, 0 is when they have not had this experience – that is, the venture capital backed company in question is their first one.

Prior Experience was estimated based on the number of years the founder was actively working before they founded the given enterprise.

- Prior Experience = Year of Foundation – Year of founder's first job.

Undergraduate is a variable that stands for the area in which the founder gained their graduation degree. We have clustered this variable in five main groups: Business, Computer and related, Engineer, Natural Science, and Arts, Marketing and others.

Expertise is a variable that measures the founder's level of education. We have categorized this into four categories: high school, undergraduate, MBA, and Academic (here we have master's degree, PhD, and Post-doctoral degree).

Foreigner is a binary variable where 1 is when the founder is a citizen of another Country, and 0 is when the founder is Brazilian.

Foreign Institution is a variable that we had a feeling might be relevant while we were manually analyzing and gathering data. We came to understand that many Brazilian entrepreneurs had their education abroad. For this reason, we created a variable indicating whether or not founders had studied in a foreign institution. Foreign Institution is a binary variable, where 1 stands for when the founder has had their education abroad. On the other hand, 0 stands for when their education took place inside Brazil.

4.2.2. Dependent Variables: Definition of Success

In order to identify the characteristics correlated with a venture's success, we first have to define success. We will develop five models based on five different definitions of success (i.e., with different dependent variables reflecting the different ways in which success has been defined/operationalized in the extant literature).

The five different models will each include the same independent variables, but with different dependent variables - although all of these will be binary in nature with Successful (1) or not (0).

Five definitions of a venture's 'success':

1. Success is determined by the total funding amount raised by a company. Since we are dealing with VC companies that were founded in different years, also

differing in their years of existence, this variable was operationalized as the average of funding per year. Thus, success is defined as:

Success1 = Total Funding amount / (2021-founding year)

To be considered successful a company should have an average funding amount equal to or above U$600.000 per year. This number was chosen as it represents the top 20% of the ventures.

2. CrunchBase has its own ranking system. Although it is not disclosed how exactly they measure this rank, our second definition of success is based on the CB's ranking.

Success2 = Top 23,000 CB Rank on Jan 2021

Since it is a worldwide Venture Capital backed company ranking, the threshold rank that embodies one third of Brazil's top companies is the Top 23,000. That is, there are about 100 of 300 Brazilian Ventures in the CB's Top 23,000.

3. Another definition of success used was a simple separation between companies that have already closed down, and those that haven't. That is, the company is successful if it is still active/open. Otherwise, it is labeled as 'closed' and not successful.

Success3 = Opened status of the company in Jan 2021.

There are some major issues with this definition. The first issue is that most companies take a long time to be officially 'closed', although they are already shut to business. So, there may be companies that appear 'Open' but in fact aren't. A second issue is due to the company's founding year. There are many different time periods between 2021 and the company's age of life, and for a company that was founded in 2020, being 'open' in 2021 does not necessarily make it more successful than a company founded in 2005 and closed in 2020.Thus, this means that it is easier for younger companies to fulfil this success criterion than countries founded many years ago.

4. Success here is defined by the number of fund-raising rounds the venture has had. We considered as successful those companies that had two or more fund-raising rounds as they represent the top third of companies in the data based on this metric.

Success4 = Number of funding rounds ≥ 2

Here, once again, we have an issue regarding the age of the companies. Bias may occur given that an older company has had more time to have a second funding round, making it harder for the younger companies to fulfil this success criterion.

5. Success is determined by the last year of the venture's revenue. It is relevant to state that there are several problems with this metric. First of all, most of the seed and early-stage companies still don't have public information about their revenue. Therefore, there is a lot of missing data. Second, Venture Capital companies are high risk high return ones, meaning that each year can be a game changer for best or worst. Third and last, the information regarding the company's revenue is given in a sequence of ranges, they are: under 1 million USD, between 1 million USD and 10 million USD, between 10 million USD and 50 million USD, between 50 million USD and 100 million USD, between 100 million USD and 500 million USD and above 500 million USD.

Success5 = elevated revenue per year

To be considered successful a company should have revenues equal to or above the range of 'between 1 million USD and 10 million USD'. We chose this parameter as it represents one third of the data.

Another step before we go into the model was also performed. Since two of our model's independent variables were non-numeric, namely Undergrad and Expertise, we first coded these into several binary variables, as follows:

Undergrad variable:

DUndergrad1 = 'business'

DUndergrad2 = 'computer'
DUndergrad3 = 'arts, marketing and others'
DUndergrad4 = 'engineer'
DUndergrad5 = 'natural science'

Expertise variable:
DExpertise1 = 'undergraduate'
DExpertise2 = 'academic'
DExpertise3 = 'mba'
DExpertise 4 = 'high school and tech'

5. Analyses – Statistical procedures

For the predictive modelling, we use a statistical parametric model, which means there is an actual mathematical simple function taking the inputs (or features) into the output (or predictive score). In this case, let the founder's features be a vector $\vec{x}_1$, then the predictive score y is given by

$$y = f(\vec{x}_1).$$

Typically, in linear models used in accounting and economics, it is assumed that the output variable is a linear function of the features (for instance, $\vec{x}_1$). Although linear regression is very useful across different topics to elucidate the basic principles of a phenomenon, the current task requires a model that captures probabilities (ranging from 0 to 1) of success and failure and possibly a nonlinear dependency between features and such probability. Among different nonlinear models, we have chosen a member of the generalized linear models called logistic regression, mostly used to model probabilities. The model is defined in terms of the log-odds transformation as

$$log \frac{y}{1-y} = \beta_0 + \vec{\beta}_1 \cdot \vec{x}_1 \,,$$

Where y is the model's guess for the probability of success ($y = 1$) or failure ($y = 0$), i.e., a binary outcome for a given venture capital backed startup. The model's parameters are the intercept (β_0), founder's parameter ($\vec{\beta}_1$).

It is also possible to rewrite the score as a function of the parameters as follows:

$$\frac{1}{1+e^{-\left(\beta_0+\vec{\beta}_1\cdot\vec{x}_1\right)}}$$

This way, it shows that the score is bounded in the domain $[0,1]$. Actually, if the exponential approaches zero, then the score approaches $y = 1$. Alternatively, if the exponential tends to infinity, the score approaches $y = 0$. The next step is to find the optimal parameters $(\beta_0, \vec{\beta}_1)$ for a definition of success. As mentioned before, the binary variable success is based on five possibilities (dependent variables): Funding/year, CB Rank, Status Opened/Closed, Funding Rounds, Revenue. As for the independent variables $(\vec{x}_1)$: the founder's features, such as age and experience, are displayed in Table 12. This model has been widely used in recent research in the area (Milosevic, 2018; Nahata, Hazarika and Tandon, 2014).

For the estimation, or learning, we used a machine learning paradigm called gradient descent. The idea is to define a cost function as a function of the estimate $y = y(x)$ and the actual value y'. Then, the score $y(x)$ is updated to minimize the cost function. In our case, we have the cross-entropy:

$$L(y, y') = log\, y(x) - \left(1 - y'(x)\right)\log(1 - y(x))$$

Notice that the cost function reduces to $L(y, 1) = -log\, y(x)$ and $L(y, 0) = -log\,(1 - y(x))$ for the cases $y' = 1$ and $y' = 0$, respectively. Which means that the score $y(x)$ will be increased whenever $y' = 1$ in the attempt to minimize $L(y, 1) = -log\, y(x)$. Alternatively, the score $y(x)$ will be decreased whenever $y' = 0$ in the attempt to minimize $L(y, 0) = -log\,(1 - y(x))$. The goal in the learning process is to find parameters $(\beta_0, \vec{\beta}_1)$ in $y(x)$ that minimize the cost function. The loss function is convex in the parameters, which means it does not have a local minimum, except for a single global minimum. This fact guarantees the convergence of the iterative incremental method:

$$\beta \to \beta - \gamma \frac{\partial L(y, y')}{\partial \beta},$$

Which means that each β in (β_0, $\vec{\beta}_1$) is updated in the direction that minimizes the cost function. Whenever the cost function hits a minimum, β is not updated (meaning $\beta \rightarrow \beta$ reaches a fixed point). The hyperparameter γ is called the learning rate.

5.1. Logistic Regression

For each model, we will show the coefficient found for each variable used in the model. Similar to a linear regression, the coefficient is the real number that multiplies the variable in the output of the model. Therefore, if a dummy variable x has coefficient b the model will use the product xb in the composition of the output. The intercept is the constant coefficient (it multiplies by 1) in the composition. Since the model is not linear, the best way to understand the coefficient is in terms of the odds ratio. If the coefficient of a dummy variable (say, Sexmale1) is b it means men (sexmale=1) have exp(b) times the odds of women (sexmale=0) of having a successful company. Of course, if $\mathrm{b} > 0$ it means there is an increase (exp(b)>1) in the odds ratio. Alternatively, if b<0, it means there is a decrease ($\exp(\mathrm{b}) < 1$) in the odds ratio.

The standard error is interpreted as the uncertainty of the logistic regression coefficient. It is used for computing the z-value (or p-value) and the underlying confidence interval for the coefficient. The z-value is the ratio between the coefficient and the standard error. The larger the z-value, the lower the uncertainty as the standard error is smaller when compared to the coefficient value.

Finally, the slope is computed as follows. Taking a dummy variable as an example (sexmale=1), compute the odds ratio for men, odds_men=P(success|sexmale=1)/P(success|sexmale=0), and do the same for women. Then, the slope is the difference between the logarithms of the odds, log(odds_men) - log(odds_women).

5.2. Confusion Matrix

The confusion matrix is a simple tool for assessment of the performance of the model. It assumes a given threshold (in this case, 0.5), such that all scores above the threshold (score > 0.5) are assigned to a predicted positive class. Similarly, all scores below the threshold are assigned to a predicted negative class. Finally, the true labels (positive or negative conditions) are compared to the predicted ones. In this case, there are four different outcomes: the predicted positive cases are true (true positive) or not (false positive). Analogously, the predicted negative cases are true (true negative) or not (false negative). The four different values are arranged in the form of a 2 x 2 matrix as displayed below:

Confusion Matrix	Predicted Positive	Predicted Negative
Condition Positive	True Positive	False Negative
Condition Negative	False Positive	True Negative

In our case, the positive condition is the success of the company. Therefore, a good model that predicts the success of a company is expected to classify them in the main diagonal: true positive cases, meaning we correctly predicted that a company was going to succeed, and true negative cases, meaning that we also correctly predicted the failure of some companies based on our success criteria. However, models are prone to errors and predicting future success in the market is a highly uncertain endeavor. For that reason, it is also expected that the model will miss some predictions, in the matrix represented by the false positive and false negative entries. In order to keep a consistent evaluation across different models, we will select some simple metrics derived from the confusion matrix, defined below:

Total cases: Is the number of companies used in the evaluation of the model.

Predicted positive: the number of companies that the model predicted to be successful (by checking the condition score > threshold).

Predicted negative: the number of companies that the model predicted to be not successful (score < threshold, which means they failed to satisfy the condition score > threshold).

Prevalence: the rate of successful companies in the dataset (Positive / Total Cases). As we use different success criteria, it is expected that the prevalence will be different for each model.

True Positive: number of companies that are correctly predicted as successful.

True Negative: number of companies that are correctly predicted as not successful.

False Positive: number of companies that are predicted as successful, but are not successful.

False Negative: number of companies that are predicted as not successful, but are successful.

True Positive Rate: Is the ratio True Positive / Condition Positive. In other words, among all successful companies, the rate (%) of them that are correctly predicted.

True Negative Rate: Is the ratio True Negative/ Condition Negative. In other words, among all not successful companies, the rate (%) of them that are correctly predicted.

Precision: Is the ratio True Positive / Predicted Positive. Differently from the true positive rate, here we compute, among all predicted positive cases, the rate (%) of them that are correctly predicted.

Accuracy: Is the ratio (True Positive + True Negative) / Total Cases. In other words, among all the cases, it is the rate of correctly predicted cases. A perfect model would have an accuracy of 100%.

6. Results

In the result section, first there will be a description of the data and some statistics to better understand the data. Then, the regression model is displayed, as well as its results.

6.1. Descriptive Statistics on data

In Table 16 that follows, we show descriptive statistics on all of our data, including the age of the founders, the year in which their VC backed company was founded, and the years of prior experience of the founders.

Table 16 - Descriptive statistics on numerical data. Source: Created by the author based on data up until 2020.

Descriptive Statistics			
	Age	Year of foundation	Prior Experience
Mean	31.37	2014.04	9.55
Standard Error	0.41	0.22	0.38
Median	31	2014	9
Mode	31	2017	7
Standard Deviation	7.17	3.85	6.63
Sample Variance	51.38	14.79	44.02
Kurtosis	2.33	2,39	1.85
Skewness	1.01	-1.21	1.01
Range	51	20	37
Minimum	15	2000	0
Maximum	66	2020	37
Sum	9695	622337	2952
Count	309	309	309
Confidence Level (95.0%)	0.80	0.43	0.74

As can be seen in Table 17, the average age of founders was 31 years at the moment they founded their Venture Capital backed company. But the majority of founders were in their twenties and thirties when they founded their enterprise. It is also possible to notice a reduction in founders over forty-five years old, suggesting that this market is a relatively young one.

Table 17 - Estimated age of founders at the moment they founded their enterprise. Source: Created by the authors based on data of 2020.

Likely Age	Quantity
<15	1
15-19	5
20-24	47
25-29	79
30-34	82
35-39	57

40-44	24
45-49	5
50-54	3
55-60	3
>60	3
Total number of founders	**309**

A great deal of binary data was analyzed. This is displayed in Tables 18 and 19 that follow.

Table 18 - Frequency on flag for foreign founders. Source: Created by the authors based on data of 2020.

Flag Foreigner (1 yes, 0 no)	
0	280 (90.6%)
1	29 (9.4%)
Total	**309 (100%)**

Analysis showed that about 10% of venture capitalists' founders are foreigners, that is, not Brazilian (see Table 18). Almost 30% of the founders had their undergraduate education abroad (see Table 19). This may give support to the interpretation that perhaps a foreign education may encourage entrepreneurial activities. Another plausible explanation is their economic standing, i.e., the suggestion that people with greater power of wealth have the opportunity to both study abroad and to establish a ventures company.

Table 19 - Frequency on flag for foreign education. Source: Created by the authors based on data of 2020.

Foreign Institution	
0	222 (71.8%)
1	87 (28.2%)
Total	**309 (100%)**

Table 20 shows that over 40% of the founders have had an earlier venture enterprise. This data may explain the wide number of VC backed companies that briefly appear in the gross set of data but lack the necessary information in order to be analyzed. That is, perhaps there are a great deal of venture companies that are founded and shut down before any relevant information about the company is made available online.

Table 20 - Experience founding a previous venture, prior to the one analyzed. Source: Created by the authors based on data of 2020.

Previous Venture (1 yes, 0 no)	
0	182 (58.9%)
1	127 (41.1%)
Total	**309 (100%)**

Our dataset makes explicit the low volume of females that have founded a Brazilian VC backed company (e.g., only 5.8% of founders were women as shown in Table 21). The vast majority of VC capital is thus invested in males, who represented 94.2% of our dataset.

Table 21 - Gender. Source: Created by the authors based on data of 2020.

Gender	
Female	18 (5.8%)
Male	291 (94.2%)
Total	**309 (100%)**

As shown in Table 22, the majority of the founders had undergraduate education related to business areas. Undergraduate degrees in engineering and computer related areas were also common among our founders.

Table 22 - Undergraduate or technical area and its frequency. Source: Created by the authors based on data of 2020.

Undergraduate area	
Arts, Marketing, and others	49 (15.9%)
Business	106 (34.3%)
Computer related	60 (19.4%)
Engineer	60 (19.4%)
Natural Science	15 (4.9%)
not applicable	19 (6.1%)
Total	**309 (100%)**

Regarding undergraduate or technical areas of knowledge we also considered technical degrees. That is why there is a higher number of 'high school' educated founders listed in Table 23 (7.4%), than the frequency of 'not applicable' (6.1%) in Table 22.

The vast majority of founders have a graduation degree.

Table 23 - Expertise and its frequency. Source: Created by the authors based on data of 2020.

Expertise	
Academic	62 (20.0%)
Graduation	151 (48.9%)
High school	23 (7.4%)
Mba	73 (23.6%)
Total	**309 (100%)**

It is also relevant to question if there are significant distinctions between the five definitions of success (Funding per year, CB Rank, Closed or Opened status, Funding rounds, and Revenue). In order to gain more information, we ran their coefficient of correlation, as shown in Table 24 below:

Table 24 - Coefficient of correlation between dependent variables. Source: Created by the authors based on data of 2020.

	Fund/Year	CB Rank	Closed/Open	F Rounds	Revenue
Funding/Year	1				
CB Rank	0.836549	1			
Closed/Open	0.306585	0.308981	1		
Funding Rounds	0.389579	0.43784	0.192002	1	
Revenue	0.739982	0.678111	0.309288	0.286011	1

It is possible to notice that there is a strong correlation between Funding per year, CB Rank and Revenue definitions of success. On the other hand, the other definitions are weakly correlated. Which means that the way we define a venture's success may completely change our perceptions of them.

6.2. Regression analyses

Here we present our results on each one of the five models we have proposed. As discussed previously, this research is going to analyze different regression models, one for each definition of success (dependent variable). Our research adopts five different definitions, and for this reason we will present five models. For each model, we will present a table with the coefficients of each variable used in the logistic regression, the standard error and z-value. Then, we will show the confusion matrix of the output of the model with the underlying metrics computed.

Model Number 1: Total Funding/ (2021 - Founding Year)

Success is determined by the total funding amount raised by a company. Since we are dealing with VC companies that were founded in different years, also differing in their years of existence, this variable was defined as the average of funding per year. Thus, it is defined as:

Success1 = Total Funding amount / (2021-founding year)

The criterion to be considered successful is an average equal to or above U$600.000 per year. This number was chosen as it represents the top 20% of the ventures.

Table 25 - Model 1: Logit regression using Funding amount as dependent variable.

Model 1	**Coefficient**	**Standard error**	**Z value**	**Slope**	**P-value**
Const	-8.52	2,618.84	0.00		1.00
Founders_Qtd	0.50	0.10	5.24	0.16	0.00 ***
Sexmale1	0.55	0.50	1.10	0.14	0.27
Age	0.04	0.02	2.06	0.01	0.04 **

Previous_venture	0.23	0.21	1.09	0.07	0.28
Prior_Exp	-0.03	0.02	-1.46	-0.01	0.15
FlagForeigner	-0.23	0.34	-0.69	-0.07	0.49
Foreignere_Instit	0.81	0.22	3.74	0.28	0.00 ***
DUndergrad_1	0.44	0.45	0.99	0.14	0.32
DUndergrad_2	-0.14	0.50	-0.28	-0.04	0.78
DUndergrad_3	-0.20	0.51	-0.40	-0.06	0.69
DUndergrad_4	-0.03	0.46	-0.06	-0.01	0.95
DExpertise_1	4.64	2,618.84	0.00	0.94	1.00
DExpertise_2	4.58	2,618.84	0.00	0.95	1.00
DExpertise_3	5.15	2,618.84	0.00	0.97	1.00

*Source: Created by the authors based on data of 2020. Omitted due to exact collinearity were: DUndergrad_5 DExpertise_4. The levels of significance are: *** < 1%, **<5%, and *<10%.*

Statistical information about the model: Standard deviation of the dependent variable (0.455), McFadden's R-Squared (0.344), Adjusted R-squared (0.257), Log likelihood (-112.49), Akaike's criterion (254.98), Schwarz's criterion (309.72), Hannan-Quinn's criterion (276.93). Null hypothesis of the residue normally distributed (Chi-squared=4.16, p-value 0.12).

Table 26 - Performance Evaluation for Model 1. Source: created by the authors.

Model 1	Predicted Positive	Predicted Negative
Condition Positive	44	39
Condition Negative	13	188

Comments on Model 1: This model was tested in a database of 282 companies (total cases). From those companies, 83 had a positive condition (successful) vs. 201 with a negative condition (not successful). The prevalence of the label of success used in Model 1 is 29%. The model achieved a True Positive rate of 53% and True Negative rate of 94%. Finally, the Precision was 77% and Accuracy 82%. Note that the Precision (77%) was larger than the Prevalence (29%). This can be interpreted as follows: if you draw a company by chance, it is going to be successful in 29% of the cases. However, if you draw a company suggested by Model 1, then the probability of success increases to 77%. In this case, we say there is a lift of +165% in the chance of predicting a successful company compared to a random guess (77%/29% - 1=1.65).

Model Number 2: CrunchBase Ranking on Jan 2021

CrunchBase platform has its own ranking system. Although they do not disclose exactly how they measure this ranking, our second definition of success is based on this CB Ranking.

Success2 = Top 23,000 CB Rank in Jan 2021

Since it is a worldwide Venture Capital Backed Company Ranking, the threshold rank that embodies one third of Brazil's top companies is the Top 23,000. That is, about 100 of 300 Brazilian Ventures are ranked in the CB Top 23,000.

Table 27 - Model 2: Logit regression using CrunchBase Ranking of January 2021 as dependent variable.

Model 2	**Coefficient**	**Standard error**	**Z value**	**Slope**	**P-value**
Const	-7.64	2,609.30	0.00		1.00
Founders_Qtd	0.65	0.10	6.29	0.21	0.00***
Sexmale1	-0.06	0.47	-0.13	-0.02	0.90
age	0.04	0.02	1.83	0.01	0.07*
Previous_venture	0.36	0.21	1.68	0.12	0.09*
Prior_Exp	-0.04	0.02	-1.74	-0.01	0.08*

FlagForeigner	-0.43	0.36	-1.20	-0.12	0.23
Foreign_Instit	0.75	0.22	3.34	0.26	0.00***
DUndergrad_1	0.17	0.44	0.38	0.05	0.70
DUndergrad_2	-0.43	0.49	-0.88	-0.13	0.38
DUndergrad_3	-0.52	0.50	-1.04	-0.15	0.30
DUndergrad_4	-0.27	0.45	-0.60	-0.08	0.55
DExpertise_1	4.54	2,609.30	0.00	0.94	1.0
DExpertise_2	4.46	2,609.30	0.00	0.94	1.0
DExpertise_3	5.17	2,609.30	0.00	0.97	1.0

*Source: Created by the authors based on data of 2020. Omitted due to exact collinearity were: DUndergrad_5 DExpertise_4. The levels of significance are: *** < 1%, **<5%, and *<10%.*

Statistical information about the model: Standard deviation of the dependent variable (0.455), McFadden's R-Squared (0.382), Adjusted R-squared (0.296), Log likelihood (-107.01), Akaike's criterion (244.01), Schwarz's criterion (298.74), Hannan-Quinn's criterion (265.95). Null hypothesis of the residue normally distributed (Chi-squared=21.67, p-value 2e-5).

Table 28 - Performance Evaluation for Model 2. Source: created by the authors.

Model 2	Predicted Positive	Predicted Negative
Condition Positive	51	34
Condition Negative	13	186

Comments on Model 2: This model was tested in a database of 284 companies (total cases). From those companies, 85 had a positive condition (successful) vs. 199 with a negative condition (not successful). The prevalence of the label of success used in Model 2 is 30%. The model achieved a True Positive rate of 60% and True Negative rate of 93%. Finally, the Precision was 80% and Accuracy 83%. As in the previous model, note that the Precision (80%) was larger than the Prevalence (30%). This is interpreted as follows: if you draw a company by chance, it is going to be successful in 30% of the cases. However, if you draw a company suggested by Model 2, then the probability of success increases to 80%. In this case, we say there is a lift of +166% in the chance of predicting a successful company compared to a random guess (80%/30% - 1=1.66). In this sense, we can say that Models 1 and 2 are similar in performance.

Model Number 3: Closed or Active on Jan 2021

Another definition of success used was a simple separation between companies that have already closed, and those that haven't. That is, the company is successful if it is still active/open, otherwise, it is labeled as 'closed' and not successful.

Success3 = Opened status of the company in Jan 2021.

As mentioned before, there are some issues with this definition regarding its potential susceptibility to biases, as young companies are likely to be open in 2021 and there is some delay in reporting of 'closed' status information.

Table 29 - Model 3: Logit regression using Closed or Active status in January 2021 as dependent variable.

Model 3	**Coefficient**	**Standard error**	**Z value**	**Slope**	**P-value**
Const	5.38	3,464.15	0.00		1.00
Founders_Qtd	0.33	0.12	2.68	0.05	0.01 ***
Sexmale1	0.43	0.37	1.17	0.10	0.24
age	-0.02	0.02	-1.08	-0.00	0.28

Previous_venture	0.07	0.21	0.31	0.01	0.76
Prior_Exp	0.05	0.02	2.25	0.00	0.02 **
FlagForeigner	-0.22	0.39	-0.57	-0.4	0.57
Foreign_Instit	0.01	0.24	0.05	0.00	0.96
DUndergrad_1	0.33	0.41	0.79	0.05	0.43
DUndergrad_2	0.30	0.44	0.68	0.05	0.50
DUndergrad_3	0.41	0.45	0.92	0.06	0.36
DUndergrad_4	0.45	0.43	1.07	0.07	0.29
DExpertise_1	-5.56	3,464.15	0.00	-0.92	1.00
DExpertise_2	-5.29	3,464.15	0.00	-0.99	1.00
DExpertise_3	-5.13	3,464.15	0.00	-0.98	1.00

*Source: Created by the authors based on data of 2020. Omitted due to exact collinearity were: DUndergrad_4, DUndergrad_5, DExpertise_3, and DExpertise_4. The levels of significance are: *** < 1%, **<5%, and *<10%.*

Statistical information about the model: Standard deviation of the dependent variable (0.378), McFadden's R-Squared (0.125), Adjusted R-squared (0.009), Log likelihood (-114.33), Akaike's criterion (258.67), Schwarz's criterion (313.40), Hannan-Quinn's criterion (265.95). Null hypothesis of the residue normally distributed (Chi-squared=5,09, p-value 0,079).

Table 30 - Performance Evaluation for Model 3. Source: created by the authors.

Model 3	Predicted Positive	Predicted Negative
Condition Positive	232	3
Condition Negative	49	0

Comments on Model 3: This model was tested in a database of 284 companies (Total Cases). From those companies, 235 had a positive condition (successful) vs. 49 with a negative condition (not successful). This shows that this definition of success, based on survivability, is very different from the definitions used in Models 1 and 2. The prevalence of the label of success used in Model 3 is 83%. The model achieved a True Positive rate of 99% and True Negative rate of 0%. Finally, the Precision was 99% and Accuracy 82%. Differently from the previous models, it should be noted that the Precision (83%) is equal to the Prevalence (83%). The interpretation of this analysis is as follows: if you draw a company by chance, it is going to be successful in 83% of the cases. However, if you draw a company suggested by Model 3, then the probability of success is again 83%. In this case, we say there is a lift of +0% in the chance of predicting a successful company compared to a random guess (83%/83% - 1=0.0). In other words, an analysis does not benefit from using Model 3 to predict successful companies. Therefore, the model is close to a random guess at the threshold of score >0.5. This shows that the criterion of survivability is essentially random in the sense that our current variables are not predicting this type of success. As mentioned in the definition of the Confusion Matrix, the threshold used to define the Predicted Positive class was 0.5. A better use of the model might be to consider a different threshold (score>0.9) which results in a different confusion matrix.

Model Number 4: Funding Rounds

Success here is defined as the number of fundraising rounds the venture has had. We considered as successful the ventures that had two or more fundraising rounds, as they represent one third of the data.

Success4 = Number of funding rounds ≥ 2

Here we have an issue regarding the age of the companies. Bias may occur given that an older company has had more time to have a second funding round, making it harder for the younger companies to fulfill this success criterion.

Table 31 - Model 4: Logit regression using Funding Rounds as dependent variable.

Model 4	**Coefficient**	**Standard error**	**Z value**	**Slope**	**P-value**
Const	-0.61	0.95	-0.64		0.52
Founders_Qtd	0.47	0.10	4.58	0.18	0.00 ***
Sexmale1	-0.23	0.36	-0.65	-0.9	0.52
age	0.01	0.02	0.66	0.00	0.51
Previous_venture	0.21	0.18	1.17	0.08	0.24
Prior_Exp	-0.04	0.02	-2.29	-0.2	0.02 **
FlagForeigner	0.49	0.34	1.45	0.2	0.15
Foreign_Instit	0.01	0.20	0.05	0.00	0.96
DUndergrad_1	0.25	0.41	0.62	0.09	0.54
DUndergrad_2	-0.15	0.43	-0.36	-0.6	0.72
DUndergrad_3	0.00	0.43	0.01	0.00	0.99
DUndergrad_4	-0.06	0.41	-0.15	-0.2	0.88
DExpertise_1	-0.26	0.58	-0.45	-0.10	0.65
DExpertise_2	-0.02	0.59	-0.03	-0.00	0.97
DExpertise_3	0.40	0.59	0.68	0.15	0.50

Source: Created by the authors based on data of 2020. Omitted due to exact collinearity were:

*DUndergrad_4, DUndergrad_5, DExpertise_3, and DExpertise_4. The levels of significance are: *** < 1%, **<5%, and *<10%.*

Statistical information about the model: Standard deviation of the dependent variable (0.500), McFadden's R-Squared (0.180), Adjusted R-squared (0.103), Log likelihood (-161.28), Akaike's criterion (352.56), Schwarz's criterion (407.29), Hannan-Quinn's criterion (374.50). Null hypothesis of the residue normally distributed (Chi-squared=4.28, p-value 0,117).

Table 32 - Performance Evaluation for Model 4. Source: created by the authors.

Model 4	Predicted Positive	Predicted Negative
Condition Positive	97	51
Condition Negative	35	101

Comments on Model 4: This model was tested in a database of 284 companies (Total Cases). From those companies, 148 had a positive condition (successful) vs. 136 with a negative condition (not successful). The prevalence of the label of success used in Model 4 is 52%, different from the prevalence of Models 1 and 2 (around 30%) and Model 3 (83%). The model achieved a True Positive rate of 66% and True Negative rate of 74%. Finally, the Precision was 73% and Accuracy 70%. Note that, as in Models 1 and 2, the Precision (73%) was larger than the Prevalence (52%). Again, if you draw a company by chance, it is going to be successful in 52% of the cases. However, if you draw a company suggested by Model 4, then the probability of success increases to 73%. In this case, we say there is a lift of +41% in the chance of predicting a successful company compared to a random guess (73%/52% - 1=0.24). Curiously, the success criterion used in Model 4 has a Prevalence similar to a coin toss (52%) and the model has an Accuracy of 70%. In this case, one might see Model 4 as guessing correctly the outcomes of a coin toss 70% of the time, which is quite a feat.

Model Number 5: Company's last year of revenue

As previously mentioned, in model 5 success is determined by the last year of the venture's revenue.

Success5 = high revenue per year

The criterion to be considered successful was equal to or above the range of 'between 1 million USD and 10 million USD'. We chose this parameter as it represents one third of the data.

Table 33 - Model 5: Logit regression using Revenue as dependent variable.

Model 5	Coefficient	Standard error	Z value	Slope	P-value
Const	-6.74	3,646.10	0.00		1.00
Founders_Qtd	0.93	0.19	4.79	0.37	0.00 ***
Sexmale1	0.76	0.78	0.98	0.28	0.33
age	0.01	0.05	0.17	0.00	0.86
Previous_venture	0.66	0.42	1.57	0.26	0.12
Prior_Exp	0.00	0.05	-0.06	0.00	0.95
FlagForeigner	-0.81	0.62	-1.31	-0.29	0.19
Foreign_Instit	0.62	0.37	1.67	0.24	0.10 *
DUndergrad_1	-1.43	0.90	-1.60	-0.51	0.11
DUndergrad_2	-1.95	0.99	-1.96	-0.61	0.05 **
DUndergrad_3	-2.11	1.07	-1.98	-0.55	0.05 **
DUndergrad_4	-0.98	0.88	-1.12	-0.36	0.26
DExpertise_1	3.81	3,646.10	0.00	0.94	1.00
DExpertise_2	3.81	3,646.10	0.00	0.78	1.00
DExpertise_3	5.05	3,646.10	0.00	0.95	1.00

*Source: Created by the authors based on data of 2020. Omitted due to exact collinearity were: DUndergrad_4, DUndergrad_5, DExpertise_3, and DExpertise_4. The levels of significance are: *** < 1%, **<5%, and *<10%.*

Statistical information about the model: Standard deviation of the dependent variable (0.484), McFadden's R-Squared (0.560), Adjusted R-squared (0.385), Log likelihood (-37.66), Akaike's criterion (105.32), Schwarz's criterion (148.33), Hannan-Quinn's criterion (122.80). Null hypothesis of the residue normally distributed (Chi-squared=9.34, p-value 0.009).

Table 34 - Performance Evaluation for Model 5. Source: created by the authors.

Model 5	Predicted Positive	Predicted Negative
Condition Positive	38	10
Condition Negative	5	77

Comments on Model 5: This model was tested in a database of 130 companies (Total Cases). This total is very different (much lower) from the previous models, because information on revenues is scarce. From these companies, 48 had a positive condition (successful) vs. 82 with a negative condition (not successful). The Prevalence of the label of success used in Model 5 is 37%. The model achieved a True Positive rate of 88% and True Negative rate of 94%. Finally, the Precision was 88% and Accuracy 88%. As in Models 1, 2 and 4, note that the Precision (88%) was larger than the Prevalence (37%). Intuitively, if you draw a company by chance, it is going to be successful in 37% of the cases. However, if you draw a company suggested by Model 5, then the probability of success increases to 88%. In this case, we say there is a lift of +139% in the chance of predicting a successful company compared to a random guess (88%/38% - 1=1.39).

7. Performance Evaluation with Cross-Validation

In this section, we select the best models obtained in the previous section and evaluate their performance in a more realistic setting. The confusion matrices obtained before were computed in the modeling dataset, which might be subject to overfitting, a situation where the model learns known data, but fails to generalize the knowledge to new data. In order to test the ability to generalize to new data, one needs to test the model in a dataset different from the one it was trained on. In our case, since we have limited data, the best strategy is to apply a N-fold cross-validation, where the modeling dataset is partitioned in N parts, as explained below. Then, we evaluate the performance of the model on test datasets using some techniques. We use the Kolmogorov-Smirnov (KS) distance, which is widely used in the financial sector, especially in the assessment of credit default models, Cross-Entropy (CE), Mean Squared Error and Area Under Receiver Operating Characteristic (AuRoc).

7.1. N-fold cross-validation

Consider a dataset with M registries (in our case, companies). A strategy of N-fold cross-validation considers a random partition of the dataset in N parts of the same size. By definition of a partition, we mean that each subset will hold approximately M/N (M over N) registries and each registry will belong to only one subset. This idea can be implemented as follows: scramble the registries randomly (using a random number generator from MS excel). Then, split the set into subsets of M/N registries. Each subset is then indexed as subset(i), for i=1,...,N.

Finally, we train N different models. Each model trains on all the subsets except for subset(i), which results in a training set size of M(1-1/N). Then, each model is tested in the subset(i) of size M/N. Note that all subsets(i) are used as a test set a single time and the collection of all predictions on the test sets will result in the full dataset. In this case, we are able to evaluate the performance of the model in the whole database as a test set knowing that all registries were not observed during the training phase. This is a realistic setting because it avoids overfitting, since the companies in the test set are not used in the training phase, at the cost of sacrificing a part of the training set, now of size M(1-1/N).

In our case, we chose N=4, which results in a training set of size 75% (1-1/N) of the full database and test sets of size 25%. Consequently, we train 4 different models of the same type (and using the same variables) as explained in the previous section. Because of retraining, although the training set is very similar to the one used in the previous section, there might be fluctuation in the parameters obtained in the final model as will be discussed below.

7.2. Kolgomogorov-Smirnov (KS) distance

In the previous section, we used the confusion matrix as a tool for performance evaluation of the models in the training set to evaluate their overall quality. This tool allows intuitive definitions of true positives and negatives that are easier to understand. However, from a technical standpoint, the confusion matrix is limited to a single threshold of the predictive score. This means an arbitrary value (for instance, threshold=0.5) is used to split the predictions into predicted positives/negatives. In a real application, predicted models are used as decision support systems (DSS) and it is unlikely that decisions will be made exactly at an arbitrary threshold. For that reason, it is relevant to evaluate the model using different metrics. A particular one used in the financial sector is the Kolmogorov-Smirnov distance, which is a function of the score ranging from 0 to 1.

The KS distance at the score X is defined as the difference between the cumulative distributions of the Condition Positive with score < X and the Condition Negative with score < X. By definition, the KS distance is bounded between 0 and 1, it is exactly 0 for X=0 and X=1. Intuitively, one could see the KS distance as a measure of distinguishability between the Condition Positive and Negative cases. If they cannot be distinguished using the score, then both cumulative distributions will have the same value at score=X, and the KS distance will result in zero. However, if you have a perfect model, there will be a score X that will split perfectly all Condition Positives (cumulative distribution of the Condition Positive = 100% for score<X) from Condition Negatives (cumulative distribution of the Condition Negative = 0% for score<X), which results in a KS distance = 1 (100%-0%). Typically, some value between 0 and 1 is observed as the maximum of the KS distance. This value is called the maximum KS distance and the underlying X is the value that maximizes the KS distance.

7.3. Area under the Receiving Operating Characteristic (AuROC)

The area under the receiving operating characteristic, also known as the area under ROC (AuROC), is widely used in the performance evaluation of binary classification tasks. It does not consider any arbitrary threshold of the score, which makes it a good tool to evaluate the whole range of predicted scores. The definition uses concepts presented in the confusion matrix. For each threshold X (ranging from 0 to 1), the True Positive Rate (TPR) and False Positive Rate (FPR) from the confusion matrix is computed and these values are plotted in a plane where the vertical axis is the TPR, and the horizontal axis is the FPR. Finally, the area under the curve is computed. Intuitively, if TPR=FPR for all values X, this means the area will be ½ (area of a triangle) and the model is ineffectual. However, if TPR > FPR, the area will be in the range 0.5 and 1. If the AuROC=1, then the TPR=1 and FPR=0 for all values X>0, which is a perfect model.

7.4. Mean Squared Error (MSE)

A standard way to check the performance of a model is to use the euclidean distance between the predicted values and the real values, $(\text{predicted} - \text{real})^2$. In this case, a binary classification task, the real values are either 0 or 1. The predicted values are given by the score, which is a value in the range [0,1]. Therefore, the Mean Squared Error (MSE) is just the mean of the euclidean distance of the errors across the whole test set. Note that if a perfect model assigns a score = 0 for all Condition Negative cases (real label = 0) and a score 1 = for all Condition Positive cases (real label = 1), then the MSE will result in 0, which is the lowest possible value.

7.5. Cross-Entropy (CE)

In classification tasks, another way to evaluate a model is to consider the cross entropy. The same concept was used to define the loss function for the logistic regression. For binary classification, this is defined as the sum over the whole test set of the quantity $-label * \log(score) - (1 - label) * \log(1 - score)$. Although not intuitive, one might check if label = 1, then the minimal value of CE is achieved for score = 1, and -log(score) > 0 for 0<score <1. Alternatively, if label = 0, then the minimal value of CE is achieved for score = 0, because log(1-score)=log(1)=0. This metric is mostly used as a loss function in algorithms of machine learning.

7.6. Results: Model 1 (Funding Amount per year)

Among the different models analyzed in the previous section, we selected Model 1, which has funding amount per year as the success criterion. This choice is motivated by the performance of this model in the training set. We apply N-fold cross-validation with N=4, then we collect the predicted scores and compute the confusion matrix. Then, we compute the mean squared error (MSE), cross-entropy, Kolmogorov-Smirnov distance and area under the ROC curve. Because of cross-validation, all results below are in the test set, which is a more realistic setting for the performance evaluation of the model.

Note that in the training set presented in the previous section, we had 282 data points used to train the model and evaluate the confusion matrix. The Predicted Positive was 57 (=44+13, which represents 20% of the database). In the present case, we have 308 data points because all of the companies were used in the prediction, even those with missing data. As all missing entries are flags (after encoding categorical variables), the missing flags are considered 0 for simplicity, although other treatments might be used. In this case, we consider a threshold such that the Predicted Positive is also 20% of the database in order to compare it to the previous confusion matrix.

Table 35 – Model 1 Cross-Validation. Source: Created by the authors.

Model 1 (Cross-Validation)	Predicted Positive	Predicted Negative
Condition Positive	41	51
Condition Negative	22	193

Comments on Model 1 (Cross-Validation): The model was tested in a database of 307 companies (Total Cases). From those companies, 92 had a positive condition (successful) vs. 215 with a negative condition (not successful). The Prevalence of the label of success used in Model 1 is 30% (close to the 29% in the training set). In the cross-validation, the model achieved a True Positive Rate of 45% (vs. 53% in the training set) and a True Negative Rate of 90% (vs. 94% in the training set). Finally, the Precision was 65% (vs. 77% in the training set) and

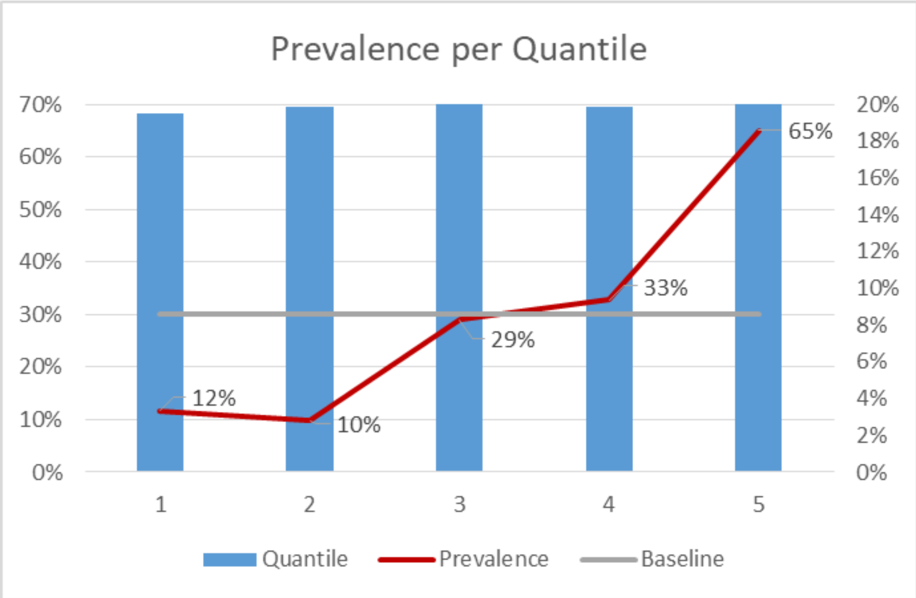
Accuracy 76% (vs. 82% in the training set). Note that the Precision (65%) was larger than the Prevalence (30%). Again, the interpretation is that if you draw a company by chance, it is going to be successful in 30% of the cases. However, if you draw a company suggested by Model 1, then the probability of success increases to 65%. In this case, we say there is a lift of +117% (vs. +165% in the training set) in the chance of predicting a successful company compared to a random guess.

The slightly lower performance obtained by the model in the cross-validation is expected for two reasons. First, statistical models learn from the training data and try to generalize knowledge to the test data, but often patterns found in new data could be new and pose a challenge to the predictive model. The second reason is that we performed the cross-validation in the whole database, including cases with missing data, which adds noise to the inputs.

Now we organize the test set in quantiles by ranking the companies from the lowest to the highest score, then splitting the ranking in equal parts. The first quantile has the companies with the lowest score and the last quantile has companies with the highest score. We chose to depict 5 quantiles (each with 20% of the companies), because of the size of the dataset. Then, we plotted the prevalence (the relative number of successful companies) per quantile in Figure 9.

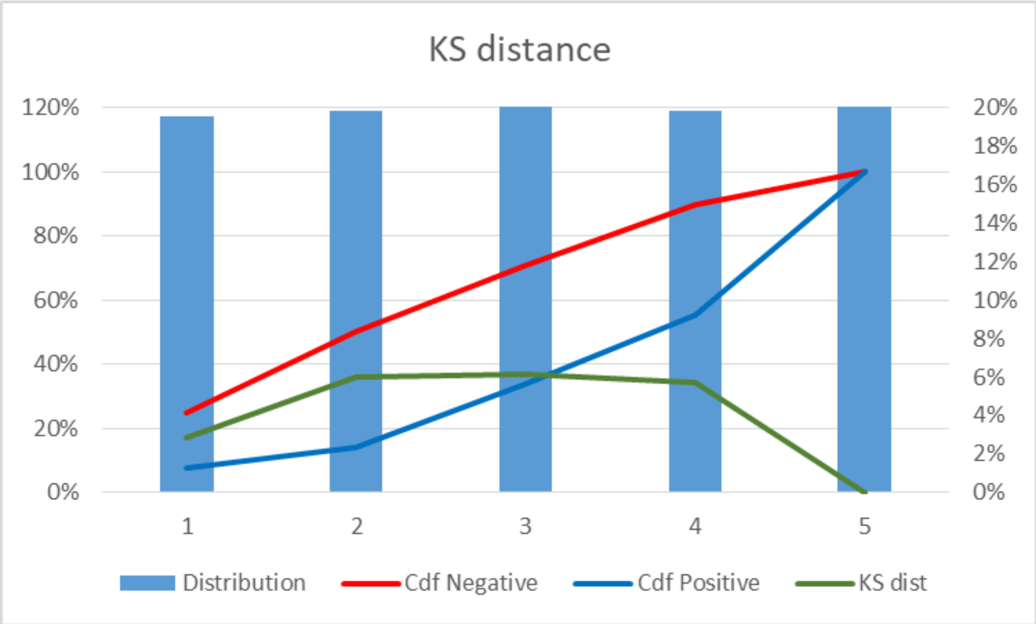
Note that the baseline had a Prevalence of 30%, but the last quantile had a Prevalence of 65%. This is already known from the confusion matrix, as the Precision of 65% was observed in the confusion matrix above, because we built it so that 20% of the cases were Predicted Positive, i.e., the last quantile of 20% of the score. The Prevalence in the other quantiles is new information, not observed in the confusion matrix. Particularly, quantiles 1 and 2 show a Prevalence in the range 10%-12%, which is almost three times lower than the baseline (30%). Quantiles 3 and 4 have a Prevalence very close to the baseline (29% and 33% vs. 30%). Therefore, loosely speaking, a company could be classified as likely successful (quantile 5), likely unsuccessful (quantiles 1 and 2) and uncertain (quantiles 3 and 4).

Figure 9 - Prevalence (relative number of successful companies) per quantile (representing 20% of the companies). The gray baseline is the Prevalence of the whole database.



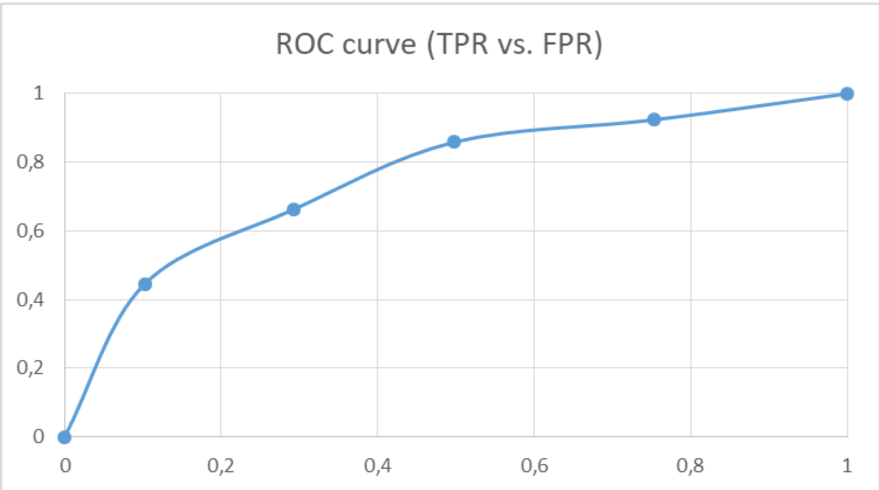
Next, we plot the KS distance in Figure 10. The cumulative density function (Cdf) for the Condition Negative (red) and Condition Positive (blue) as a function of the five quantiles. The difference between both Cdfs is the Kolmogorov-Smirnov (KS) distance. A poor performing model would not distinguish between Positive and Negative cases, which would result in collapsing Cdfs such that KS max = 0. A perfect model would split all Negative and Positive cases correctly, yielding KS max = 100%. The maximum value observed for our model was KS max = 37%.

Figure 10 - Kolmogorov-Smirnov (KS) distance for Model 1 in the cross-validation dataset. The cumulative density function (Cdf) for the Condition Negative (red) and Condition Positive (blue) as a function of the five quantiles. The difference between both Cdfs is the Kolmogorov-Smirnov (KS) distance.



Finally, the Receiving Operating Characteristic (ROC) curve is depicted as the True Positive Rate on the Y axis and False Positive Rate on the X axis for different thresholds (please see Figure 11). The area under this curve (AuROC) is an important performance evaluation toll. A model with AuROC 0.5 is ineffectual, while a model with AuROC 1.0 is perfect. Our model achieved AuRoc=0.82.

Figure 11 - Receiving Operating Characteristic (ROC) curve for Model 1 in the cross-validation dataset.



A summary of the performance evaluation metrics for Model 1 in the cross-validation dataset is given below.

Table 36 - Performance evaluation metrics for Model 1 in the cross-validation database.

Mean Squared Error (MSE)	0.17
Cross-Entropy (CE)	0.33
KS Max	0.37
AuROC	0.83

Based on this analysis we can conclude that using different evaluation metrics, a good performance of Model 1 in the cross-validation database was achieved even when compared to the training set. This shows that the model did not overfit the training data and the variables selected as inputs were reasonable predictors for the success of the companies. Predictive models are often tools of decision support systems. As such, an example of a practical application, for instance, in Venture Capital allocation, is that companies in the last quantile (top 20% of the predicted scores) are very likely to be successful and should be preferred. However, if a company is found in the first two quantiles (lower 40% of the companies ranked by the predictive score), they are likely to be unsuccessful.

8. Discussion

Five different models were discussed to predict and understand potentially ‘successful’ ventures. Each one of the model explored a different definition of a VC backed company’s ‘success’, which were: Funding amount, CB ranking, Survivability, Revenue, and Number of funding rounds. As independent variables we chose non-financial information – such as the founders’ team composition, founders’ education and expertise, founders’ age, and others.

In tests of four of these hypotheses our chosen independent variables were found to be significant in predicting a venture capital backed company’s success. The significant models were (1) Funding amount, (2) CB ranking, (3) Revenue, and (4) Number of funding rounds.

In order to evaluate each of our model's outcomes, we have used a confusion matrix. As previously displayed, the confusion matrix is a simple tool to assess the performance of the models. We analyzed several metrics and focused on the models' 'lift' i.e., their chances of predicting a successful company compared to a random guess.

Table 37 - Models' lift performance. Source: Created by the authors based on our developed models.

Models	Lift
Funding amount	+165%
CB ranking	+166%
Survivability	0.0
Revenue	+41%
Number of funding rounds	+139%

Our chosen independent variables were found to be most strongly related to a venture's funding amount. This means that the independent variables (number of founders, gender, age, previous venture experience, expertise, foreign founders, foreign education of founders, and founders' undergraduate area) were able to efficiently predict the venture companies that received the greatest funding capital.

Table 38 – Summary of the independent variables' relationships with success in each model, highlighting the direction of the association (positive versus negative) and its significance.

Model	Variables		
	Positive	**Negative**	**Significant**
1	Founders_Qtd, Sexmale1, Age, Previous_venture, Foreign_Instit, DUndergrad_1 (Business), DExpertise_1, DExpertise_2, DExpertise_3	Prior_Exp, FlagForeigner, DUndergrad_2, DUndergrad_3, DUndergrad_4	Founders_Qtd, Age, Foreign_Instit
2	Founders_Qtd, Age, Previous_venture, Foreign_Instit, DUndergrad_1, DExpertise_1, DExpertise_2, DExpertise_3	Sexmale1, Prior_Exp, FlagForeigner, DUndergrad_2, DUndergrad_3, DUndergrad_4	Founders_Qtd, Age, Previous_venture, Prior_Exp, Foreign_Instit
3	Founders_Qtd, Sexmale, Previous_venture, Prior_Exp,	Age, FlagForeigner, DExpertise_1,	Founders_Qtd, Prior_Exp

	Foreign_Instit, DUndergrad_1, DUndergrad_2, DUndergrad_3, DUndergrad_4	DExpertise_2, DExpertise_3	
4	Founders_Qtd, Age, Previous_venture, FlagForeigner, Foreign_Instit, DUndergrad_1, DUndergrad_3, DExpertise_3	Sexmale1, Prior_Exp, DUndergrad_2, DUndergrad_4, DExpertise_1, DExpertise_2	Founders_Qtd, Prior_Exp
5	Founders_Qtd, Sexmale1, Age, Previous_venture, Prior_Exp, Foreign_Instit, DExpertise_1, DExpertise_2, DExpertise_3	FlagForeigner, DUndergrad_1, DUndergrad_2, DUndergrad_3, DUndergrad_4	Founders_Qtd

Notes: Founders_Qtd = number of founders equal to or higher than 2; Sexmale1 = gender of founder is male; Age = age of the founder at the moment they founded the given venture; Previous_venture = binary variable where 1 stands for the founders who had previous experience founding another ventures company; FlagForeigner = binary variable where 1 stands for founder's nationality being from abroad; Foreign_Instit = binary variable where 1 stands for the founder's undergraduate education being carried out abroad; DExpertise_1 = if the founder's highest education level is undergraduate degree; DExpertise_2 = if the founder's highest education level is academic degree (master, doctoral, PhD, or post-doc), DExpertise_3 = if the founder's highest education level is a MBA degree; DUndergrad_1 = when the area of the founder's undergraduate degree is in business; DUndergrad_2 = when the area of the founder's undergraduate degree is any computer related area; DUndergrad_3 = when the area of the founder's undergraduate degree is in arts, marketing, and others; DUndergrad_4 = when the area of the founder's undergraduate degree is in engineering.

In models 1, 2, and 3, the variables undergraduate (DExpertise_1), academic (DExpertise_2), and MBA (DExpertise_3), were all positively associated with success (above 3). This can be explained by the nature of the variable that was left out (high school/tech DExpertise_4), which is included in the information regarding the constant of the model. DExpertise_4, as explained before, stands for founders that had an education level up to high-school degree. This means that all founders with higher or further education showed greater prospects of success, especially those founders with an MBA (DExpertise_3).

Another relevant discovery was regarding the variable 'Foreign Institution', which appeared to be positive regardless of the success approach taken and which was found to be significant in models 1 and 2. This is an interesting finding. This variable was chosen based on intuition, after several months of data mining on LinkedIn. Based on this analysis it seemed probable that whether or not the founders had previously studied at a foreign (as opposed to a home) institution may be important to their success, and this turned out to be true. Another strong intuition, but one we did not follow up on, was concerning where the founder attended high school. We have the feeling that founders attending high-profile schools may have some correlation with their VC backed company's success, especially the ones in the South-East and South of Brazil. This is a valuable angle to explore in future research.

We had previously predicted a positive relationship between the founder's status as a foreigner (versus Brazilian) and success, but this was not the case in the majority of our results. With the exception of model 4, the remaining models showed a negative association between this variable and success. Previous years of work experience (Prior_exp) is another good example. This variable shows a positive and significant correlation with success in model 3 but a negative and significant correlation with success in models 2 and 4.

It is noticeable that depending on the definition of success, different outcomes are presented. Take the independent variable Age, for example. It was found to have a positive and significant association with success in models 1 and 2, a negative association with success in model 3, and a non-significant positive association with success in models 4 and 5.

The independent variable number of founders (Founders_Qtd) was both positive and significant in all of the five models. This finding can be explained by network theory, and the observation that a combination of individuals and groups working together offer competitive advantages to benefit one another.

CHAPTER 4 - GENERAL DISCUSSION

1. Summary of findings

This thesis has analyzed Venture Capital (VC) from two different perspectives: both theoretical, and practical. We investigated different criteria for defining successful VC backed companies. We then focused on venture capital backed companies in Brazil and examined if it is possible to predict success based on known information and statistical modeling. We discovered it is possible to achieve a good performance in the prediction of a company's success criteria and the underlying variables that allowed the prediction, although some success criteria are harder to predict than others. These findings shed light on VC decision- making as they allow us to understand and predict the potential success of a Brazilian VC backed company from its foundation. Researchers and practitioners from the VC industry could adapt our predictive models and use them in their decision support system toolboxes with the aim of ensuring better capital allocation and risk management, especially in emerging markets. A detailed summary of each chapter follows.

The first chapter provided insights into the landscape of the venture capital market, as well as the landscape of current research in this area. We also showed that the total amount of VC funding has increased enormously, especially in the last few years, setting surprising new records during the Covid-19 pandemic (2020-2021). From a data science perspective, this step is also known as business understanding in data science projects. It allows the researcher to map the decision-making process, the business goals and overall context. In this case, the main theories used in the literature of venture capital (VC) were identified and explored. We showed that numerous theories have been applied; Some have deep roots in economics and finance, and some are mainly managerial, but only a few of them could be argued to have been developed with VCs in mind.

We then, in the second chapter, provide a systematic review of an important issue regarding VC backed companies' lack of common metrics and common definitions of success. With this review, we have learned that there are four primary definition-clusters of success that are commonly used in academic research. These are: exits, survivability, amount of funding capital raised, and self-reported or self-developed success scales. Each approach has its benefits, but also drawbacks. Some definitions of success are associated with more limitations than others. Another contribution of this chapter was that we showed that the academic landscape of VCs lacks a common language, lacks a common scale, and also that when different definitions of success are considered the antecedents identified as being important for VC-backed companies' success are also often found to be different. This makes it difficult to develop and consolidate a strong academic knowledge base and understanding of VCs.

Finally, in the third chapter, we present an empirical study focusing on venture capital-backed companies in the Brazilian context. In particular, we advance understanding of companies' success through predictive modeling and performance evaluation. We measured variables describing each company as well as different success criteria in order to create a predictive model for success. In each case, we trained a logistic regression model and analyzed the resulting confusion matrix for each score in the training set. Then, we selected the most promising model and retrained it with a cross-validation method (four-fold) in order to assess the model's performance in a test set. For the performance evaluation, we computed the success rate per score, cross-entropy (CE), mean squared error (MSE), area under the receiving operating curve (AuROC) and the Kolmogorov-Smirnov (KS) maximum distance. In all metrics, the model achieved a good performance with a reasonable and intuitive interpretation of how to use it as a decision support system for VCs.

2. Contributions

This thesis provides a number of contributions and insights that may be pursued further in future research. After setting out the landscape of VCs, we offered a comprehensive and systematic review of the literature. Then we followed up on this by delving into Brazilian venture capital backed companies. As the literature on VCs in emerging markets is scarce, our review provides new insights for researchers in this area. It is important to note that the widespread use of

IPO/acquisition as the criterion for success when judging private companies in the US is valid because the US market is mature. However, one could not easily apply the same criterion for emerging markets where success cases would be almost absent, because few companies have grown to experience an IPO episode or are acquired in these markets. Therefore, our systematic review and, in particular, our empirical analysis, provide very valuable insights for other developing economies and the venture capital backed companies that operate in them. In addition, this research is timely, as Brazilian backed companies have been taking off in the last few years.

2.1. Theoretical contributions

We have found that, although there are theories applied to the Venture Capital phenomenon, there is a wide variety of them and there is a lack of academic consensus on the main theories that explain the Venture Capital phenomenon. We also argue that most of the theories applied have their roots in other phenomena (financial, economic, and managerial) and there is still a need to consolidate theories that explain and fit optimally with the venture capital phenomenon.

Better understanding of the correlation between the stock market and the Venture Capital market is also needed. We have shown that there is a noticeable association between the development and crashes of the public stock enterprises and the venture capital market, but we also noticed a detached and opposite behavior as well. Greater knowledge on how, why, and when these markets are combined or not is needed.

Research suggests that there may be a relationship between venture capital and cutting-edge technological value creating. This creates grounds to explore the positive and negative side of human technological evolution, as well as an exploration of the ethical boundaries and implications of such endeavors.

One of the main issues VC research faces today is the lack of a conceptual framework, theory, and especially common language and definitions. One of these language gaps is extensively debated here – i.e., the definition of a Venture Capital backed company's *Success.* Further discussion and development of a convergent, widely accepted conceptual framework is fundamental in order to gain a better understanding and efficiency in the VC field of study. From a theoretical standpoint, we also investigated several possible predictors of success related to the companies' foundations, including the founders' backgrounds and demographics. The predictors were general enough so that they could be tested as predictors of all criteria of success, although their relevance in the prediction depended on the specific criterion. These findings are outlined in the next section.

Our last point is regarding the need for an open minded, humble and balanced perception that reaches beyond a financial and economic positivist lens, beyond financial and numerical information, and beyond mainstream valuation models. We need a better understanding of how non-financial data can be validated and used to enhance knowledge of a company's potential and improve decision-making processes.

2.2. Practical contributions

Regarding our empirical research, we proposed five hypotheses that gave rise to five different models to predict and understand the 'success' of ventures. These models explored if different definitions of 'success' could be partially determined by the company's team composition, founding team size, management team size, CEO's education and expertise, team experience and by the VC's size, type, age and country of origin. The five models explored different dependent variables, which were: Funding amount, CB ranking, Survivability, Revenue, and Number of funding rounds.

Our chosen independent variables were found to be most strongly related to a venture's funding amount. This means that the independent variables (number of founders, gender, age, previous venture experience, expertise, foreign founders, foreign education of founders, and founder's undergraduate discipline) are able to efficiently predict the venture companies that receive the greatest amount of funding capital.

It could be argued that this positive association may be due to social bias, networking advantages, or greater potential. That is, a founder's profile may lead to him/her having greater access to resources, prospectus network contacts, and more opportunities for investments (as predicted by networking theory), rather than being innately/intrinsically better able to run a successful VC backed company. The reasons for this positive association need further investigation.

From the results, we found that the model that predicts the success criterion of funding amount had good performance. Through different evaluation metrics, Model 1 achieved a good performance even when compared to the training set. As mentioned in Chapter 3, an example of a practical application in venture capital allocation is that the last quantile (top 20% of the predicted scores) of companies are very likely to be successful and should be preferred. However, if a company is found in the lower 40% of the companies ranked by the predictive score, they are likely to be unsuccessful. Although the model combines all predictors, some of them are more relevant. For instance, the chance of success is likely to be higher if the founder had a previous venture, is a male, studied in a foreign institution and had a business background, when success is measured in funding amount.

Survivability was the one model that had no greater outcome than random chance. We argue that this may be due to an issue with the temporal lag between shutting down a company's activity and officially/formally closing it. This lag may lead to misleading data regarding the number of 'opened' versus 'closed' companies than may in fact be the reality.

One limitation of our empirical work was due to restrictions in our access to data. Although CrunchBase provides a great deal of information on Brazilian ventures, a great deal of missing data is still an issue. This is especially the case due to our approach, which involved matching CrunchBase data with a Linkedin search for additional information on the founders. In order to embark on this Linkedin matching process, a certain amount of information on the founders was needed from the outset, in order to find their Linkedin profile.

2.2.1. Contributions for academics

We showed that there are four different clusters of success definitions that are used in academic research. These are: exits, survivability, amount of funding capital raised, and self-reported or self-developed sales. Each approach has upsides and drawbacks. Some definitions of success have more limitations than others, as we summarize in the following text.

An exit event as an indicator of a venture's success is an ideal metric, as it shares a common base with traditional finance, where solid/objective and in some cases detailed financial information is made public. This is especially the case for IPO events (initial public offerings). Although an ideal approach, exit events are the last phase of a venture capital backed company and they only happen for those enterprises that have survived and prospered sufficiently to do so. In a market like the Brazilian one, where venture capital has only taken flight in the last decade or so, and the number of venture capital backed companies that have been through an IPO can be counted on one hand, using exit events is unfeasible. This is the case for many other (especially emerging) markets and is why there is still limited research that makes use of this approach, as we have shown in our systematic review.

Survivability has also been used as a metric to define a venture capital backed company's success. There isn't a universal definition of survivability. Some academic researchers use a period of n year(s) after their founding date, some use a period of years common to all (for example, survived from 2010 to 2012). In our empirical research we used Active or Closed as a metric for survivability, but the results were not satisfying at all. We found that there is no predictive power between the chosen independent variables and this outcome of a venture enterprise.

Total funding amount raised by a venture capital backed company is also a common and feasible approach. In our empirical research we found this to be the most promising dependent variable. There are mainly two reasons for that: the first is that it is an accessible information source, venture capital companies tend to disclose the amount of their investments in each venture. The second reason is that we found a high correlation and predictive power between the chosen independent variables and the amount of funding raised by a venture capital backed company.

The last cluster of venture capital backed company's success metrics relate to self-reported or self-developed scales. Although these two approaches are a clever way to go when there is a lack of financial data from the venture capital backed companies, we have found that there is still the need for a convergent validated scale. In our systematic review we found some controversial results among the research studies that made use of this approach, which makes it hard to generalize their results.

3. Limitations and Future Directions

Why is there an association between funding amount raised and the chosen independent variables? Is it because there is indeed greater potential of thriving amongst the group of founders that share similar characteristics, or could there be a systematic bias in the process of venture capital companies choosing who they want to fund? For instance, if founders with a business background are getting more funding in the present, the predictive models and VC practitioners would notice and develop some intuition behind it. Then, the next rounds of VC would allocate capital to founders with a business background, creating a self-fulfilling prediction. Alternatively, niche VC funds could attempt to challenge biased predictors and fund underrepresented groups, allowing A/B testing to take place. This matter needs further investigation.

Another limitation of past VC research, which is highlighted in this thesis, is the need to develop and validate a common measure to assess a venture capital backed company's success by interview or survey. Currently, success criteria based on surveys lack generality and consensus, as they seem to show a wide range of unrelated results. In some respects, the results coming from self-reported and self-developed scales seem purely random. For instance, we found that some predictors suggested by data driven success criteria are dismissed in studies where success criteria are based on surveys. Therefore, there is a need to address the lack of common ground, as well as the lack of valid and reliable measures used in surveys assessing success.

The data suggests that there may be a correlation between venture capital and cutting-edge technological value creation. That is, technological VC-backed companies tend to be high performing in the current markets, as well as representing the vast majority of the VC's capital market share. This creates grounds to explore the upsides and drawbacks of human technological evolution, as well as an exploration of the ethical limits and effects of such activities.

Finally, we restate the need for an open minded and balanced perception that reaches beyond a financial and economic positivist lens, beyond financial and numerical information, and beyond mainstream valuation models. We need a better understanding of how non-financial data can be validated and used to enhance knowledge of a company's potential and improve decision making processes.

REFERENCES

Abdou, K., & Varela, O. (2009). Is there a puzzle in the failure of venture capital backed portfolio companies? *Applied Financial Economics*, *19*(18), 1439-1452. *

Abell, P., & Nisar, T. M. (2007). Performance effects of venture capital firm networks. *Management Decision*.

Aernoudt, R. (2005). Executive forum: Seven ways to stimulate business angels' investments. *Venture Capital*, *7*(4), 359-371.

Afful-Dadzie, E., & Afful-Dadzie, A. (2016). A decision making model for selecting start-up businesses in a government venture capital scheme. *Management Decision*.

Ahlers, G. K., Cumming, D., Günther, C., & Schweizer, D. (2015). Signaling in equity crowdfunding. *Entrepreneurship Theory and Practice*, *39*(4), 955-980.

Ahlstrom, D., & Bruton, G. D. (2002). An institutional perspective on the role of culture in shaping strategic actions by technology-focused entrepreneurial firms in China. *Entrepreneurship Theory and Practice*, *26*(4), 53-68.

Ahlstrom, D., & Bruton, G. D. (2006). Venture capital in emerging economies: Networks and institutional change. *Entrepreneurship Theory and Practice*, *30*(2), 299-320.

Arthurs, J. D., & Busenitz, L. W. (2003). The boundaries and limitations of agency theory and stewardship theory in the venture capitalist/entrepreneur relationship. *Entrepreneurship Theory and Practice*, *28*(2), 145-162.

Ball, R., & Brown, P. (1968). An empirical evaluation of accounting income numbers. *Journal of Accounting Research*, *6*(2), 159-178.

Ball, R., & Brown, P. (2019). Ball and Brown (1968) after fifty years. *Pacific-Basin Finance Journal*, *53*, 410-431.

Baluku, M. M., Kikooma, J. F., & Kibanja, G. M. (2016). Psychological capital and the startup capital–entrepreneurial success relationship. *Journal of Small Business & Entrepreneurship*, *28*(1), 27-54.

Barker, R. G. (1999). The role of dividends in valuation models used by analysts and fund managers. *European Accounting Review*, *8*(2), 195-218.

Barth, M. E., Beaver, W. H., & Landsman, W. R. (2001). The relevance of the value relevance literature for financial accounting standard setting: another view. *Journal of Accounting and Economics*, *31*(1-3), 77-104.

Bates, T., & Bradford, W. D. (1992). Factors affecting new firm success and their use in venture capital financing. *The Journal of Entrepreneurial Finance*, *2*(1), 23-38.

Battisti, E., Nirino, N., Leonidou, E., & Thrassou, A. (2022). Corporate venture capital and CSR performance: An extended resource based view's perspective. *Journal of Business Research*, *139*, 1058-1066.

Bausch, A., & Krist, M. (2007). The effect of context-related moderators on the internationalization-performance relationship: Evidence from meta-analysis. *Management International Review*, *47*(3), 319-347.

Bellavitis, C., Filatotchev, I., & Kamuriwo, D. S. (2014). The effects of intra-industry and extra-industry networks on performance: A case of venture capital portfolio firms. *Managerial and Decision Economics*, *35*(2), 129-144.

Bergemann, D., & Hege, U. (1998). Venture capital financing, moral hazard, and learning. *Journal of Banking & Finance*, *22*(6-8), 703-735.

Bergemann, D., & Hege, U. (2005). The financing of innovation: Learning and stopping. *RAND Journal of Economics*, 719-752.

Berger, A. N., & Schaeck, K. (2011). Small and medium-sized enterprises, bank relationship strength, and the use of venture capital. *Journal of Money, Credit and banking*, *43*(2-3), 461-490.

Bertoni, F., Colombo, M. G., & Quas, A. (2019). The role of governmental venture capital in the venture capital ecosystem: An organizational ecology perspective. *Entrepreneurship Theory and Practice*, *43*(3), 611-628.

Beyer, A., Cohen, D., Lys, T., & Walther, B. (2010). The financial reporting environment: Review of the recent literature. *Journal of Accounting and Economics*, 50(2–3), 296–343.

Bhide, A. (1994). How entrepreneurs craft strategies that work. *Harvard Business Review*, *72*(2), 150-161.

Boissin, R., & Sentis, P. (2014). Long-run performance of IPOs and the role of financial analysts: some French evidence. *The European Journal of Finance*, *20*(2), 125-149.

Bottazzi, L., & Da Rin, M. (2002). Venture capital in Europe and the financing of innovative companies. *Economic Policy*, *17*(34), 229-270.

Brander, J. A., Amit, R., & Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, *11*(3), 423-452.

Brau, J. C., Brown, R. A., & Osteryoung, J. S. (2004). Do venture capitalists add value to small manufacturing firms? An empirical analysis of venture and nonventure capital-backed initial public offerings. *Journal of Small Business Management*, *42*(1), 78-92.

Brush, C. G., & Vanderwerf, P. A. (1992). A comparison of methods and sources for obtaining estimates of new venture performance. *Journal of Business Venturing*, *7*(2), 157-170.

Bruton, G. D., Filatotchev, I., Chahine, S., & Wright, M. (2010). Governance, ownership structure, and performance of IPO firms: The impact of different types of private equity investors and institutional environments. *Strategic Management Journal*, *31*(5), 491-509.

Bruton, G. D., Fried, V. H., & Manigart, S. (2005). Institutional influences on the worldwide expansion of venture capital. *Entrepreneurship Theory and Practice*, *29*(6), 737-760.

Burt, R. S., & Celotto, N. (1992). The network structure of management roles in a large matrix firm. *Evaluation and Program Planning*, *15*(3), 303-326.

Busenitz, L. W., Moesel, D. D., Fiet, J. O., & Barney, J. B. (1997). The framing of perceptions of fairness in the relationship between venture capitalists and new venture teams. *Entrepreneurship Theory and Practice*, *21*(3), 5-22.

Busenitz, L. W., Fiet, J. O., & Moesel, D. D. (2004). Reconsidering the venture capitalists' “value added” proposition: An interorganizational learning perspective. *Journal of Business Venturing*, *19*(6), 787-807.

Bygrave, W. D. (1988). The structure of the investment networks of venture capital firms. *Journal of Business Venturing*, *3*(2), 137-157.

Cable, D. M., & Shane, S. (1997). A prisoner's dilemma approach to entrepreneur-venture capitalist relationships. *Academy of Management review*, *22*(1), 142-176.

Casamatta, C. (2003). Financing and advising: optimal financial contracts with venture capitalists. *The Journal of Finance*, *58*(5), 2059-2085.

Celikyurt, U., Sevilir, M., & Shivdasani, A. (2014). Venture capitalists on boards of mature public firms. *The Review of Financial Studies*, *27*(1), 56-101.

Chemmanur, T. J., & Chen, Z. (2014). Venture capitalists versus angels: The dynamics of private firm financing contracts. *The Review of Corporate Finance Studies*, *3*(1-2), 39-86.

Chen, J. V., Nguyen, T. T. L., & Ha, Q. A. (2022). The impacts of shared understanding and shared knowledge quality on emerging technology startup team's performance. Knowledge Management Research & Practice, 20(1), 104-122.

Choi, Y., & Kim, D. (2018). The effects of investor types on investees' performance: Focusing on the seed accelerator. *Cogent Economics & Finance*, *6*(1), 1550870.

Clarysse, B., Bobelyn, A., & del Palacio Aguirre, I. (2013). Learning from own and others' previous experience: the contribution of the venture capital firm to the likelihood of a portfolio company's trade sale. *Small Business Economics*, *40*(3), 575-590.

Clements, M. P., & Reade, J. J. (2016). Forecasting and forecast narratives: The Bank of England inflation reports. *Henley Business School, University of Reading, Discussion Paper ICM-2016-10*.

Cooper, A. C., Folta, T. B., & Woo, C. (1995). Entrepreneurial information search. *Journal of Business Venturing*, *10*(2), 107-120.

Cornelius, B., & Persson, O. (2006). Who's who in venture capital research. *Technovation*, *26*(2), 142-150.

Cornelli, F., & Yosha, O. (2003). Stage financing and the role of convertible securities. *The Review of Economic Studies*, *70*(1), 1-32.

Croce, A., Guerini, M., & Ughetto, E. (2018). Angel financing and the performance of high-tech start-ups. *Journal of Small Business Management*, *56*(2), 208-228.

Cumming, D., Fleming, G., & Suchard, J. A. (2005). Venture capitalist value-added activities, fundraising and drawdowns. *Journal of Banking & Finance*, *29*(2), 295-331.

Cummings, D. J., & MacIntosh, J. G. (2003). Venture-capital exits in Canada and the United States. *U. Toronto LJ*, *53*, 101.

Da Rin, M., Hellmann, T., & Puri, M. (2013). A survey of venture capital research. In *Handbook of the Economics of Finance* (Vol. 2, pp. 573-648). Elsevier.

Dainelli, F., Bini, L., & Giunta, F. (2013). Signaling strategies in annual reports: Evidence from the disclosure of performance indicators. *Advances in Accounting*, *29*(2), 267-277.

Dashti, Y., & Schwartz, D. (2018). Should start-ups embrace a strategic approach toward integrating foreign stakeholders into their network? *Innovation*, *20*(2), 164-191.

De Clercq, D., & Sapienza, H. J. (2001). The creation of relational rents in venture capitalist-entrepreneur dyads. *Venture Capital: An International Journal of Entrepreneurial Finance*, *3*(2), 107-127.

De Clercq, D., & Sapienza, H. J. (2005). When do venture capital firms learn from their portfolio companies? *Entrepreneurship Theory and Practice*, *29*(4), 517-535.

De Clercq, D., & Sapienza, H. J. (2006). Effects of relational capital and commitment on venture capitalists' perception of portfolio company performance. *Journal of Business Venturing*, *21*(3), 326-347.

De Lima Ribeiro, L., & Gledson de Carvalho, A. (2008). Private equity and venture capital in an emerging economy: evidence from Brazil. *Venture Capital*, *10*(2), 111-126.

Denyer, D., & Tranfield, D. (2009). Producing a systematic review. In D. A. Buchanan & A. Bryman (Eds.), *The Sage handbook of organizational research methods. Sage Publications Ltd.* (pp. 671–689).

Demirakos, E. G., Strong, N. C., & Walker, M. (2004). What valuation models do analysts use? *Accounting Horizons*, *18*(4), 221-240.

Dessi, R. (2005). Start-up finance, monitoring, and collusion. *RAND Journal of Economics*, 255-274.

Echols, A., & Tsai, W. (2005). Niche and performance: the moderating role of network embeddedness. *Strategic Management Journal*, *26*(3), 219-238.

Engel, D. (2004). The performance of venture-backed firms: the effect of venture capital company characteristics. *Industry and Innovation*, *11*(3), 249-263.

Espenlaub, S., Khurshed, A., & Mohamed, A. (2015). VC investments and global exits. *The European Journal of Finance*, *21*(7), 608-628.

Eid, F. (2006). Private equity finance as a growth engine: What it means for emerging markets. *Business Economics*, *41*(3), 7-22.

Elitzur, R., & Gavious, A. (2003). A multi-period game theoretic model of venture capitalists and entrepreneurs. *European Journal of Operational Research*, *144*(2), 440-453.

Ewens, M., Nanda, R., & Rhodes-Kropf, M. (2018). Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics*, *128*(3), 422-442.

Ewens, M., Gorbenko, A., & Korteweg, A. (2022). Venture capital contracts. *Journal of Financial Economics, 143*(1), 131-158.

Fairchild, R. (2011). An entrepreneur's choice of venture capitalist or angel-financing: A behavioral game-theoretic approach. *Journal of Business Venturing*, *26*(3), 359-374.

Falconieri, S., Filatotchev, I., & Tastan, M. (2019). Size and diversity in VC syndicates and their impact on IPO performance. *The European Journal of Finance*, *25*(11), 1032-1053.

Fan, P., & Yamada, K. (2020). Same bed different dream composition of IPO shares and withdrawal decisions in weak market conditions. *Small Business Economics*, *55*(4), 955-974.

Ferrary, M., & Granovetter, M. (2009). The role of venture capital firms in Silicon Valley's complex innovation network. *Economy and Society*, *38*(2), 326-359.

Ferrati, F., & Muffatto, M. (2020, June). Using Crunchbase for research in Entrepreneurship: data content and structure. In *19th European Conference on Research Methodology for Business and Management Studies (ECRM), Aveiro, Portugal (18-19 June)* (pp. 342-351).

Ferrati, F., & Muffatto, M. (2021). Reviewing equity investors' funding criteria: a comprehensive classification and research agenda. *Venture Capital*, *23*(2), 157-178.

Fiet, J. O., Busenitz, L. W., Moesel, D. D., & Barney, J. B. (1997). Complementary theoretical perspectives on the dismissal of new venture team members. *Journal of Business Venturing*, *12*(5), 347-366.

Fleming, L., & Frenken, K. (2007). The evolution of inventor networks in the Silicon Valley and Boston regions. *Advances in Complex Systems*, *10*(01), 53-71.

French, N., & Gabrielli, L. (2005). Discounted cash flow: accounting for uncertainty. *Journal of Property Investment & Finance, 23*(1), 76-89.

Gereto, M. A. S. (2019). *Caracterização do ciclo de investimentos de venture capital em startups brasileiras em termos de rodadas de investimentos e estratégias de desinvestimento a partir de dados da Crunchbase* (Doctoral dissertation).

Gerpott, T. J., & Niegel, C. (2002). Mobile business start-ups in Germany: An exploration of the start-up scene and of corporate venture capital firms' views on business success drivers and inhibitors. *International Journal on Media Management*, *4*(4), 235-247.

Gimeno, J., Folta, T. B., Cooper, A. C., & Woo, C. Y. (1997). Survival of the fittest? Entrepreneurial human capital and the persistence of underperforming firms. *Administrative Science Quarterly*, 42(4), 750-783.

Gimmon, E., & Levie, J. (2009). Instrumental value theory and the human capital of entrepreneurs. *Journal of Economic Issues*, *43*(3), 715-732.

Gindling, T. H., & Newhouse, D. (2014). Self-employment in the developing world. *World Development*, *56*, 313-331.

Gioielli, S. O., De Carvalho, A. G., & Sampaio, J. O. (2013). Venture capital and earnings management in IPOs. Available at SSRN 1134932.

Gohil, R. K., & Vyas, V. (2016). Private equity performance: A literature review. *The Journal of Private Equity*, *19*(3), 76-88.

Gloor, P. A., Colladon, A. F., Grippa, F., Hadley, B. M., & Woerner, S. (2020). The impact of social media presence and board member composition on new venture success: Evidences from VC-backed US startups. *Technological Forecasting and Social Change*, *157*, 120098.

Gompers, P. A. (1994). The rise and fall of venture capital. *Business and Economic History*, 1-26.

Gompers, P. (2007). Venture capital. In *Handbook of Empirical Corporate Finance* (pp. 481-509). Elsevier.

Gompers, P. A. (2022). Optimal investment, monitoring, and the staging of venture capital. In Venture Capital (pp. 285-313). Routledge.

Gompers, P., & Lerner, J. (2000). The determinants of corporate venture capital success: Organizational structure, incentives, and complementarities. In *Concentrated corporate ownership* (pp. 17-54). University of Chicago Press.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2005). Venture capital investment cycles: The role of experience and specialization. *Journal of Financial Economics*, *81*(1), 649-679.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2008). Venture capital investment cycles: The impact of public markets. *Journal of Financial Economics*, *87*(1), 1-23.

Gompers, P., Kovner, A., Lerner, J., & Scharfstein, D. (2010). Performance persistence in entrepreneurship. *Journal of Financial Economics*, *96*(1), 18-32.

Gompers, P. A., Mukharlyamov, V., & Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, *119*(3), 626-644.

Gorman, M., & Sahlman, W. A. (1989). What do venture capitalists do? *Journal of Business Venturing*, *4*(4), 231-248.

Gough, D., Thomas, J., & Oliver, S. (2012). Clarifying differences between review designs and methods. *Systematic Reviews*, *1*(1), 1-9.

Gvazdaityte, A. (2011). Strategies on Building Venture Capital Industry in the Canary Islands. *The Journal of Private Equity*, *14*(4), 79-87.

Harrison, R. T., & Mason, C. M. (2019). Venture Capital 20 years on: reflections on the evolution of a field. *Venture Capital*, *21*(1), 1-34.

Harrison, R. T., Mason, C., & Smith, D. (2015). Heuristics, learning and the business angel investment decision-making process. *Entrepreneurship & Regional Development*, *27*(9-10), 527-554.

Hellmann, T. (2006). IPOs, acquisitions, and the use of convertible securities in venture capital. *Journal of Financial Economics*, *81*(3), 649-679.

Hellmann, T., & Puri, M. (2002). Venture capital and the professionalization of start-up firms: Empirical evidence. *The Journal of Finance*, *57*(1), 169-197.

Hisrich, R. D., & Jankowicz, A. D. (1990). Intuition in venture capital decisions: An exploratory study using a new technique. *Journal of Business Venturing*, *5*(1), 49-62.

Hochberg, Y. V., Ljungqvist, A., & Lu, Y. (2007). Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, *62*(1), 251-301.

Huang, H. C., Lai, M. C., & Lo, K. W. (2012). Do founders' own resources matter? The influence of business networks on start-up innovation and performance. *Technovation*, *32*(5), 316-327.

Humphery-Jenner, M., & Suchard, J. A. (2013). Foreign VCs and venture success: Evidence from China. *Journal of Corporate Finance*, *21*, 16-35.

IESE Annual Report 2019 - 2020. *IESE Annual Report*. https://www.iese.edu/about/annual-report/

Isaksson, A., Cornelius, B., Landström, H., & Junghagen, S. (2004). Institutional theory and contracting in venture capital: the Swedish experience. *Venture Capital*, *6*(1), 47-71.

Janiszewski, V. J., Carrascoso, L. A., Júnior, L. A. F., Lagioia, U. C. T., & Oliveira, M. F. J. (2017). Relação da Teoria da Sinalização com o Desempenho das Empresas a partir dos seus Indicadores de Performance de Divulgação Voluntária. *Revista Contabilidade e Controladoria*, *9*(2).

Jarchow, S., & Röhm, A. (2020). Business builders, contractors, and entrepreneurs—An exploratory study of IP venturing funds. *Journal of Small Business Management*, 1-46.

Johnson, W. C., & Sohl, J. (2012). Angels and venture capitalists in the initial public offering market. *Venture Capital*, *14*(1), 27-42.

Kaplan, S. N., & Lerner, J. (2016). Venture capital data: Opportunities and challenges. *Measuring entrepreneurial businesses: Current knowledge and challenges*, 413-431.

Kaplan, S. N., & Stromberg, P. (2009). Leveraged buyouts and private equity. *Journal of Economic Perspectives*, *23*(1), 121-46.

Karsai, J., Wright, M., & Filatotchev, I. (1997). Venture capital in transition economies: The case of Hungary. *Entrepreneurship Theory and Practice*, *21*(4), 93-110.

Köhn, A. (2018). The determinants of startup valuation in the venture capital context: a systematic review and avenues for future research. *Management Review Quarterly*, *68*(1), 3-36.

Koller, T. A., Copeland, T. E., Copeland, T., Koller, T., Murrin, J., & Wiley, J. (2000). *Valuation: measuring and managing the value of companies* (Vol. 79). John Wiley and Sons.

Kemeny, T., Nathan, M., & Almeer, B. (2017). *Using Crunchbase to explore innovative ecosystems in the US and UK* (No. 2017-01). Birmingham Business School Discussion Paper Series.

Kerr, W. R., Lerner, J., & Schoar, A. (2014). The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), 20-55.

Kerr, W. R., & Nanda, R. (2015). Financing innovation. *Annual Review of Financial Economics*, *7*, 445-462.

Kessler, A. (2007). Success factors for new businesses in Austria and the Czech Republic. *Entrepreneurship and Regional Development*, *19*(5), 381-403.

Kiese, M., & Wrobel, M. (2011). A public choice perspective on regional cluster and network promotion in Germany. *European Planning Studies*, *19*(10), 1691-1712.

Kirihata, T. (2007). The commercialization process of intellectual property by new technology based firms in Japan. *The Kyoto Economic Review*, *76*(2), 241-249.

Kleidon, A. W. (1986). Variance bounds tests and stock price valuation models. *Journal of Political Economy*, *94*(5), 953-1001.

Klein, J., Stuckenborg, L., & Leker, J. (2020). Hot or not–Which features make FinTechs attractive for investors? *The Journal of Entrepreneurial Finance*, *22*(1), 1.

Köhn, A. (2018). The determinants of startup valuation in the venture capital context: a systematic review and avenues for future research. *Management Review Quarterly*, *68*(1), 3-36.

Kollmann, T., & Kuckertz, A. (2004). Venture capital decision making after the high-tech downturn: considerations based on German e-business investment cases. *The Journal of Private Equity*, *7*(4), 48-59.

Korteweg, A., & Nagel, S. (2016). Risk-adjusting the returns to venture capital. *The Journal of Finance*, *71*(3), 1437-1470.

Kuckertz, A., & Kohtamaki, M. (2010). The fast eat the slow-the impact of strategy and innovation timing on the success of technology-oriented ventures. *International Journal of Technology Management*, *52*(1/2), 175-188.

LABS (2019). Brazil ranks third in the number of unicorns in 2019. Lab News. https://labsnews.com/en/news/business/brazil-ranks-third-in-the-number-of-unicorns-in-2019/

Landström, H. (1992). The relationship between private investors and small firms: an agency theory approach. *Entrepreneurship & Regional Development*, *4*(3), 199-223.

Landström, H. (Ed.). (2007). *Handbook of research on venture capital*. Edward Elgar Publishing.

Large, D., & Muegge, S. (2008). Venture capitalists' non-financial value-added: an evaluation of the evidence and implications for research. *Venture Capital*, *10*(1), 21-53.

Leonel, S. G. (2019). O papel e as contribuições da indústria de Venture Capital no Brasil. *Revista Economia Ensaios, Uberlândia*, *33*, 125-142.

Lerner, J. (1996). The government as venture capitalist: The long-run effects of the SBIR program.

Lerner, J. (2022). The syndication of venture capital investments. In *Venture Capital* (pp. 207-218). Routledge.

Levitt, B., & March, J. G. (1988). Organizational learning. *Annual Review of Sociology*, *14*, 319-340.

Linn, N. (1999). Building a network theory of social capital. *Connections*, *22*(1), 28-51.

Lockett, A., & Wright, M. (1999). The syndication of private equity: evidence from the UK. *Venture Capital: An International Journal of Entrepreneurial Finance*, *1*(4), 303-324.

Löher, J., Schneck, S., & Werner, A. (2018). A research note on entrepreneurs' financial commitment and crowdfunding success. *Venture Capital*, *20*(3), 309-322.

Lowry, M., & Shu, S. (2002). Litigation risk and IPO underpricing. *Journal of Financial Economics*, *65*(3), 309-335.

Manigart, S., De Waele, K., Wright, M., Robbie, K., Desbrières, P., Sapienza, H. J., & Beekman, A. (2002). Determinants of required return in venture capital investments: a five-country study. *Journal of Business Venturing*, *17*(4), 291-312.

Mainelli, M., & Pumphrey, S. (2002). Optimising risk/reward in high-ratio relationships: Jumbo Bonsai meets Pocket Battleship. *Journal of Change Management*, *3*(1), 7-20.

Marx, L. M. (1998). Efficient venture capital financing combining debt and equity. *Review of Economic Design*, *3*(4), 371-387.

Maula, M., Autio, E., & Murray, G. (2003). Prerequisites for the creation of social capital and subsequent knowledge acquisition in corporate venture capital. *Venture Capital: An International Journal of Entrepreneurial Finance*, *5*(2), 117-134.

Meade, N. (1977). The decline of venture capital. *Omega*, *5*(6), 663-672.

McKaskill, T. (2009). *Raising Angel & venture capital finance*. Melbourne: Breakthrough Publications.

McKay, R. B., & Chung, E. (2005). Benchmarking for entrepreneurial survival: Pursuing a cohesive and imperfectly imitable culture. *Benchmarking: An International Journal*.

Meade, N. (1977). The decline of venture capital. *Omega*, *5*(6), 663-672.

Merz, C., Schroeter, A., & Witt, P. (2010). Starting a New Company—Which Types of Personal Experience Help? *Journal of Enterprising Culture*, *18*(03), 291-313.

Metrick, A., & Yasuda, A. (2011). Venture capital and other private equity: a survey. *European Financial Management*, *17*(4), 619-654.

Metrick, A., & Yasuda, A. (2021). *Venture capital and the finance of innovation*. John Wiley & Sons.

Miloud, T., Aspelund, A., & Cabrol, M. (2012). Startup valuation by venture capitalists: an empirical study. *Venture Capital*, *14*(2-3), 151-174.

Milosevic, M. (2018). Skills or networks? Success and fundraising determinants in a low performing venture capital market. *Research Policy*, *47*(1), 49-60.

Mitchell, J. R., Friga, P. N., & Mitchell, R. K. (2005). Untangling the intuition mess: Intuition as a construct in entrepreneurship research. *Entrepreneurship Theory and Practice*, *29*(6), 653-679.

Mitnick, B. M. (1975). The theory of agency: A framework. *The Theory of Agency (Cambridge University Press)*.

Moore, D. P. (2000). *Careerpreneurs: Lessons from Leading Women Entrepreneurs on Building a Career without Boundaries*. Davies-Black Publishing, 3803 East Bayshore Road, Palo Alto, CA 94303.

Morgan, R. M., & Hunt, S. D. (1994). The commitment-trust theory of relationship marketing. *Journal of Marketing*, *58*(3), 20-38.

Nahata, R., 2008, Venture capital reputation and investment performance. *Journal of Financial Economics*, 90(2), 127-151

Nahata, R., Hazarika, S., & Tandon, K. (2014). Success in global venture capital investing: do institutional and cultural differences matter? *Journal of Financial and Quantitative Analysis*, *49*(4), 1039-1070.

Nambisan, S., Bacon, J., & Throckmorton, J. (2012). The role of the innovation capitalist in open innovation. *Research-Technology Management*, *55*(3), 49-57.

Nanda, R., Samila, S., & Sorenson, O. (2020). The persistent effect of initial success: Evidence from venture capital. *Journal of Financial Economics*, *137*(1), 231-248.

Narayanasamy, C., Hashemoghli, A., & Mohd Rashid, R. (2011, November). Venture capital pre-investment decision making process: an exploratory study in Malaysia. In *13th Malaysian Finance Association Conference*.

Nathan, M., Kemeny, T., & Almeer, B. (2017). Using Crunchbase to explore innovative ecosystems.

Nigam, N., Benetti, C., & Johan, S. A. (2020). Digital start-up access to venture capital financing: What signals quality? *Emerging Markets Review*, *45*, 100743.

Nitani, M., Riding, A., & He, B. (2019). On equity crowdfunding: investor rationality and success factors. *Venture Capital*, *21*(2-3), 243-272.

Palepu, K. G., Healy, P. M., Wright, S., Bradbury, M., & Coulton, J. (2020). *Business analysis and valuation: Using financial statements*. Cengage AU.

Panda, S. (2018). Adequacy of agency theory in explaining the venture capitalist-entrepreneur relationship: a firm life-cycle perspective. *International Journal of Entrepreneurship and Small Business*, *34*(3), 309-329.

Parhankangas, A., & Landström, H. (2006). How venture capitalists respond to unmet expectations: The role of social environment. *Journal of Business Venturing*, *21*(6), 773-801.

Paul, S., Whittam, G., & Wyper, J. (2007). Towards a model of the business angel investment process. *Venture Capital*, *9*(2), 107-125.

Penman, S. H. (2001). On comparing cash flow and accrual accounting models for use in equity valuation: A response to Lundholm and O'Keefe (CAR, Summer 2001). *Contemporary Accounting Research*, *18*(4), 681-692.

Penman, S. H., & Penman, S. H. (2010). *Financial statement analysis and security valuation*. New York: McGraw-Hill/Irwin.

Prohorovs, A., Bistrova, J., & Ten, D. (2019). Startup Success Factors in the Capital Attraction Stage: Founders' Perspective. *Journal of East-West Business*, *25*(1), 26-51.

Puri, M., & Zarutskie, R. (2012). On the life cycle dynamics of venture-capital-and non-venture-capital-financed firms. *The Journal of Finance*, *67*(6), 2247-2293.

Rasmussen, C. C., Ladegård, G., & Korhonen-Sande, S. (2018). Growth intentions and board composition in high-growth firms. *Journal of Small Business Management*, *56*(4), 601-617.

Reiff, A., & Tykvová, T. (2021). IPO withdrawals: Are corporate governance and VC characteristics the guiding light in the rough sea of volatile markets? *Journal of Corporate Finance*, *67*, 101908.

Repullo, R., & Suarez, J. (2004). Venture capital finance: A security design approach. *Review of Finance*, *8*(1), 75-108.

Rind, K. W. (1981). The role of venture capital in corporate development. *Strategic Management Journal*, *2*(2), 169-180.

Ritter, J. R. (2011). Equilibrium in the IPO Market. *Available at SSRN 1822542*.

Robbie, K., Wright, M., & Albrighton, M. (1999). High-tech management buy-outs. *Venture Capital: An International Journal of Entrepreneurial Finance*, *1*(3), 219-239.

Robbie, K., Wright, M., & Chiplin, B. (1997). The monitoring of venture capital firms. *Entrepreneurship Theory and Practice*, 21(4), 9-28.

Rossi, M., Thrassou, A., & Vrontis, D. (2011). Financing innovation: venture capital investments in biotechnology firms. *International Journal of Technology Marketing 6*(4), 355-377.

Sahlman, W. A. (1990). The Structure and Governance of Venture-Capital Organizations. *Journal of Financial Economics* (October), *27,* 473-521.

Sapienza, H. J., & Amason, A. C. (1993). Effects of innovativeness and venture stage on venture capitalist-entrepreneur relations. *Interfaces*, *23*(6), 38-51.

Sapienza, H., Amason, A., & Manigart, S. (1994). The level and nature of venture capitalist involvement in their portfolio companies: A study of three European countries. *Managerial Finance*, *20*(1), 3-17.

Sapienza, H. J., Audrey Korsgaard, M., Goulet, P. K., & Hoogendam, J. P. (2000). Effects of agency risks and procedural justice on board processes in venture capital-backed firms. *Entrepreneurship & Regional Development*, *12*(4), 331-351.

Sapienza, H. J., & Timmons, J. A. (1989, August). The roles of venture capitalists in new ventures: What determines their importance? In *Academy of Management Proceedings* (Vol. 1989, No. 1, pp. 74-78). Briarcliff Manor, NY 10510: Academy of Management.

Schefczyk, M. (2001). Determinants of success of German venture capital investments. *Interfaces*, *31*(5), 43-61.

Schmidt, K. M. (2003). Convertible securities and venture capital finance. *The Journal of Finance*, *58*(3), 1139-1166.

Schwienbacher, A. (2010). Venture capital exits. *Venture Capital: Investment Strategies, Structures, and Policies*, 387-405.

Smart, G. H., Payne, S. N., & Yuzaki, H. (2000). What makes a successful venture capitalist? *The Journal of Private Equity*, *3*(4), 7-29.

Sorensen, M. (2007). How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finance*, *62*(6), 2725-2762.

Sorensen, M. (2008, February). Learning by investing: Evidence from venture capital. In *AFA 2008 New Orleans Meetings Paper*.

Sørheim, R. (2012). Venture capitalists as smart investors. In Handbook of Research on Venture Capital: Volume 2. Edward Elgar Publishing.

Souakri, A. (2020). Cognitive Biases in the Venture Capitalist–Entrepreneur Dyad: The Role of Entrepreneurs' Experience in VCs' Investment Decisions. In *The Entrepreneurial Behaviour: Unveiling the cognitive and emotional aspect of entrepreneurship*. Emerald Publishing Limited.

Spence, A.M. (1973). Job market signalling. *Quarterly Journal of Economics*, 87(3), 355–374.

Streletzki, J. G., & Schulte, R. (2013). Start-up teams and venture capital exit performance in Germany: venture capital firms are not selecting on the right criteria. *Journal of Small Business & Entrepreneurship*, *26*(6), 601-622.

Suder, A., & Kahraman, C. (2016). Multicriteria analysis of technological innovation investments using fuzzy sets. *Technological and Economic Development of Economy*, *22*(2), 235-253.

Sweeting, R. C. (1991). Early-stage new technology-based businesses: Interactions with venture capitalists and the development of accounting techniques and procedures. *The British Accounting Review*, *23*(1), 3-21.

Thng, T. (2019). Do VC-backed IPOs manage tone? *The European Journal of Finance*, *25*(17), 1655-1682.

Tinkler, J. E., Whittington, K. B., Ku, M. C., & Davies, A. R. (2015). Gender and venture capital decision-making: The effects of technical background and social capital on entrepreneurial evaluations. *Social Science Research*, *51*, 1-16.

Tjade, O. B., & Thrane, S. (2010). Does venture capitalist industry specialization increase the value of venture capitalist post-investment activity in portfolio firms? Unpublished thesis, Copenhagen Business School.

Tykvová, T. (2018). Legal framework quality and success of (different types of) venture capital investments. *Journal of Banking & Finance*, *87*, 333-350.

Van Osnabrugge, M. (2000). A comparison of business angel and venture capitalist investment procedures: an agency theory-based analysis. *Venture Capital: An International Journal of Entrepreneurial Finance*, *2*(2), 91-109.

Walske, J. M., & Zacharakis, A. (2009). Genetically engineered: Why some venture capital firms are more successful than others. *Entrepreneurship Theory and Practice*, *33*(1), 297-318.

Weber, C., & Weber, B. (2005). Corporate venture capital organizations in Germany. *Venture Capital: An International Journal of Entrepreneurial Finance*, *7*(1), 51-73.

Weber, B., & Weber, C. (2007). Corporate venture capital as a means of radical innovation: Relational fit, social capital, and knowledge transfer. *Journal of Engineering and Technology Management*, *24*(1-2), 11-35.

Weber, C., & Weber, B. (2010). Social capital and knowledge relatedness as promoters of organizational performance: An explorative study of corporate venture capital activity. *International Studies of Management & Organization*, *40*(3), 23-49.

Werth, J. C., & Boeert, P. (2013). Co-investment networks of business angels and the performance of their start-up investments. *International Journal of Entrepreneurial Venturing* *5*(3), 240-256.

West, G. P., & Noel, T. W. (2009). The impact of knowledge resources on new venture performance. *Journal of Small Business Management*, *47*(1), 1-22.

Wessner, C. W. (2005). Driving innovations across the valley of death. *Research-Technology Management*, *48*(1), 9-12.

Wiltbank, R., Read, S., Dew, N., & Sarasvathy, S. D. (2009). Prediction and control under uncertainty: Outcomes in angel investing. *Journal of Business Venturing*, *24*(2), 116-133.

Witt, P. (2004). Entrepreneurs' networks and the success of start-ups. *Entrepreneurship & Regional Development*, *16*(5), 391-412.

Yoo, C., Yang, D., Kim, H., & Heo, E. (2012). Key value drivers of startup companies in the new media industry—The case of online games in Korea. *Journal of Media Economics*, *25*(4), 244-260.

Zacharakis, A. L., McMullen, J. S., & Shepherd, D. A. (2007). Venture capitalists' decision policies across three countries: an institutional theory perspective. *Journal of International Business Studies*, *38*(5), 691-708.

Zarei, H., Rasti-Barzoki, M., & Moon, I. (2020). A game theoretic approach to the selection, mentorship, and investment decisions of start-up accelerators. *IEEE Transactions on Engineering Management*, *69*(4), 1753-1768.

Zarutskie, R. (2007). Do venture capitalists affect investment performance? Evidence from first-time funds. *Fuqua School of Business, Duke University*.

Zider, B. (1998). How venture capital works. *Harvard Business Review*, *76*(6), 131-139.

Appendix 1 – Calculation of the Odds Ratio and Confidence Interval

Odds Ratio

The odds ratio (OR) is a measure of how strongly an event is associated with exposure. It is an association between an exposure and an outcome. That is, it is a ratio of two sets of odds: the odds of the event occurring in an exposed group versus the odds of the event occurring in a non-exposed group (Andrade, 2015). For instance: the odds of a venture enterprise that was founded by two or more founders being successful (as we define success) versus the odds of venture companies with only one founder being successful.

The odds ratio helps identify how likely an exposure is to lead to a specific event. In this study, the odds ratio helps identify if a certain founder's characteristic may lead to a likelihood of success. The larger the odds ratio, the higher odds that the event will occur with exposure.

An odds ratio greater than 1 implies there are greater odds of the event happening in the exposed versus the non-exposed group. When it's less than 1 it implies that the odds of the event happening in the exposed group are less than in the non-exposed group. And when the OR is exactly 1 it means the odds of both exposed and non-exposed are the exact same for the studied outcome.

OR Function

Odds Ratio is equal to the odds of the event in the exposed group divided by the odds of the event in the non-exposed group. That is:

$$OR = (a/c) / (b/d)$$

Where:

a = Number of exposed cases

b = Number of exposed non-cases

c = Number of unexposed cases

d = Number of unexposed non-cases

Example: Calculating the OR of founders' level of education and their ventures' success.

Data showed that, among a sample of 97 cases, there were 43 founders that held a MBA, master's degree, or a Phd degree. Among this group, 26 are founders of what we consider a successful Venture Capital backed companies, and 17 are founders of VC backed companies not considered successful.

In the other hand, 47 founders have only a graduation degree or less – high school, technical degree. Among this group, 11 hold a successful Venture, and 36 do not.

Founder's Level of Education

	Good (successful)	Bad (not successful)
MBA or higher	26	17
Graduation or lower	11	36

Source: Created by the authors, data from CrunchBase, 2020.

With this information we can calculate the OR to identify if the first group has a higher likelihood of success.

a = 26; b = 17; c = 11; d = 36

OR = (26/11) / (17/36) = 5,005

Thus, the odds of a successful ventures are 5.00 higher given the founder's level of education being MBA, master's, or Phd compared to founders with no such degrees.

Odds Ratio Confidence Interval

The confidence interval gives an expected range for the true odds ratio for the population to fall within.

In order to calculate the confidence interval, the alpha, or our level of significance, is specified. An alpha of 0.05 means the confidence interval is 95% (1 – alpha) the true odds ratio of the overall population is within range. A 95% confidence is traditionally chosen in the medical literature (but other confidence intervals can be used). The following formula is used for a 95% confidence interval (CI). (Szumilas, 20 10)

Upper 95% CI = e ^ [ln(OR) + 1.96 sqrt(1/a + 1/b + 1/c + 1/d)]
Lower 95% CI = e ^ [ln(OR) - 1.96 sqrt(1/a + 1/b + 1/c + 1/d)]

Where 'e' is the mathematical constant for the natural log, 'ln' is the natural log, 'OR' is the odds ratio calculated, 'sqrt' is the square root function and a, b, c and d are the values discussed in the topic adove. Calculating the 95% confidence interval we get:

- Upper 95% CI =

e ^ [ln(OR) + 1.96 sqrt(1/a + 1/b + 1/c + 1/d)] =
e ^ [ln(5.00) + 1.96 sqrt(1/26 + 1/17 + 1/11 + 1/36] = 12.43

- Lower 95% CI =

e ^ [ln(OR) - 1.96 sqrt(1/a + 1/b + 1/c + 1/d)] =
e ^ [ln(5.00) - 1.96 sqrt(1/26 + 1/17 + 1/11 + 1/36)] = 2.01
Thus the odds ratio is 5.00 with a 95% confidence interval of [2.01, 12.43].

References:

Andrade C. Understanding relative risk, odds ratio, and related terms: as simple as it can get. J Clin Psychiatry. 2015 Jul;76(7):e857-61.

Szumilas M. (2010). Explaining odds ratios. Journal of the Canadian Academy of Child and Adolescent Psychiatry = Journal de l'Academie canadienne de psychiatrie de l'enfant et de l'adolescent, 19(3), 227–229.

Appendix 2 – Cross-Validation 4 fold regressions

Modelo 1: Logit, usando as observações 1-231 (n = 213)
Observações ausentes ou incompletas foram ignoradas: 18
Variável dependente: Founyear
Erros padrão baseados na Hessiana
Omitido devido a colinearidade exata: DUndergrad_5 DExpertise_4

```
              coeficiente   erro padrão      z      p-valor
  ---------------------------------------------------------------
  const           −26,0589    13853,1      −0,001881  0,9985
  Founders_Qtd       0,897190      0,209429    4,284    1,84e-05 ***
  Sexmale1          1,81214       1,34867     1,344     0,1791
  age              0,0953849     0,0427256   2,233     0,0256   **
  Previous_venture    0,513367      0,457513    1,122     0,2618
  Prior_Exp         −0,104403      0,0517478  −2,018     0,0436
**
  FlagForeigner      −0,866897      0,695873   −1,246     0,2128
  Foreignere_Instit    1,94117       0,507285    3,827     0,0001
***
  DUndergrad_1       0,303281      0,951247    0,3188    0,7499
  DUndergrad_2       1,29301       0,940409    1,375     0,1691
  DUndergrad_3      −0,0556134     1,07138    −0,05191
0,9586
  DUndergrad_4       0,128941      1,01736     0,1267    0,8991
  DExpertise_1      17,1878     13853,1       0,001241  0,9990
  DExpertise_2      17,3853     13853,1       0,001255  0,9990
  DExpertise_3      17,8104     13853,1       0,001286  0,9990
```

Média var. dependente   0,291080   D.P. var. dependente   0,455330
R-quadrado de McFadden 0,378051   R-quadrado ajustado   0,261287
Log da verossimilhança −79,89779   Critério de Akaike   189,7956
Critério de Schwarz   240,2150   Critério Hannan-Quinn   210,1717

Número de casos 'corretamente previstos' = 177 (83,1%)
f(beta'x) na média das variáveis independentes = 0,165
Teste de razão de verossimilhança: Qui-quadrado(14) = 97,1317 [0,0000]

```
          Previsto
            0    1
  Efetivo 0  141
10
        1   26    36
```

Excluindo a constante, a variável com maior p-valor foi 21 (DExpertise_1)

Modelo 2: Logit, usando as observações 1-230 (n = 219)
Observações ausentes ou incompletas foram ignoradas: 11
Variável dependente: Founyear
Erros padrão baseados na Hessiana
Omitido devido a colinearidade exata: DUndergrad_5 DExpertise_4

	coeficiente	erro padrão	z	inclinação
const	−27,5257	16066,9	−0,001713	
Founders_Qtd	0,989144	0,214322	4,615	0,152652
Sexmale1	2,02949	1,31425	1,544	0,175000
age	0,0882217	0,0428077	2,061	0,0136151
Previous_venture	0,323210	0,438618	0,7369	0,0509188
Prior_Exp	−0,0611516	0,0447470	−1,367	−0,00943740
FlagForeigner	−0,154316	0,717919	−0,2149	−0,0228927
Foreignere_Instit	1,42973	0,450928	3,171	0,258950
DUndergrad_1	1,57550	0,675088	2,334	0,274377
DUndergrad_2	0,197959	0,815749	0,2427	0,0316064
DUndergrad_3	−0,000944611	1,07682	−0,0008772	−0,000145742
DUndergrad_4	−0,000495998	0,758861	−0,0006536	−7,65395e-05
DExpertise_1	18,4895	16066,9	0,001151	0,999613
DExpertise_2	19,2396	16066,9	0,001197	0,998424
DExpertise_3	18,4000	16066,9	0,001145	0,995839

Média var. dependente 0,301370 D.P. var. dependente 0,459904
R-quadrado de McFadden 0,389617 R-quadrado ajustado 0,277704
Log da verossimilhança −81,81112 Critério de Akaike 193,6222
Critério de Schwarz 244,4583 Critério Hannan-Quinn 214,1534

Número de casos 'corretamente previstos' = 186 (84,9%)
f(beta'x) na média das variáveis independentes = 0,154
Teste de razão de verossimilhança: Qui-quadrado(14) = 104,443 [0,0000]

		Previsto	
		0	1
Efetivo	0	145	8
	1	25	41

Excluindo a constante, a variável com maior p-valor foi 19 (DUndergrad_4)

Modelo 3: Logit, usando as observações 1-230 (n = 212)
Observações ausentes ou incompletas foram ignoradas: 18
Variável dependente: Founyear
Erros padrão baseados na Hessiana
Omitido devido a colinearidade exata: DUndergrad_5 DExpertise_4

	coeficiente	erro padrão	z	inclinação
const	−5,61361	1,99286	−2,817	
Founders_Qtd	0,741058	0,181794	4,076	0,108158
Sexmale1	0,367612	0,930370	0,3951	0,0483476
age	0,0724552	0,0405971	1,785	0,0105749
Previous_venture	0,554346	0,422928	1,311	0,0833392
Prior_Exp	−0,0558908	0,0450711	−1,240	−0,00815732
FlagForeigner	−0,743600	0,728697	−1,020	−0,0881415
Foreignere_Instit	1,28748	0,426715	3,017	0,220884
DUndergrad_1	0,252495	1,00485	0,2513	0,0377145
DUndergrad_2	−0,888212	1,14781	−0,7738	−0,106045
DUndergrad_3	−0,117176	1,02696	−0,1141	−0,0167507
DUndergrad_4	−0,0957897	1,08198	−0,08853	−0,0137375
DExpertise_1	−0,838379	0,601691	−1,393	−0,104932
DExpertise_2	0,834861	0,467284	1,787	0,137869
DExpertise_3	−19,1150	17603,6	−0,001086	−0,252937

Média var. dependente 0,278302 D.P. var. dependente 0,449224
R-quadrado de McFadden 0,318439 R-quadrado ajustado 0,198788
Log da verossimilhança −85,44356 Critério de Akaike 200,8871
Critério de Schwarz 251,2359 Critério Hannan-Quinn 221,2369

Número de casos 'corretamente previstos' = 170 (80,2%)
f(beta'x) na média das variáveis independentes = 0,146
Teste de razão de verossimilhança: Qui-quadrado(14) = 79,842 [0,0000]

		Previsto	
		0	1
Efetivo	0	141	12
	1	30	29

Excluindo a constante, a variável com maior p-valor foi 23 (DExpertise_3)

Modelo 4: Logit, usando as observações 1-230 (n = 211)
Observações ausentes ou incompletas foram ignoradas: 19

Variável dependente: Founyear
Erros padrão baseados na Hessiana
Omitido devido a colinearidade exata: DUndergrad_5 DExpertise_4

	coeficiente	erro padrão	z	inclinação
const	−24,4265	19807,3	−0,001233	
Founders_Qtd	0,933246	0,209579	4,453	0,164302
Sexmale1	0,625021	0,959339	0,6515	0,0937686
age	0,0465226	0,0390238	1,192	0,00819051
Previous_venture	0,166164	0,442028	0,3759	0,0294708
Prior_Exp	−0,0256047	0,0468511	−0,5465	−0,00450782
FlagForeigner	−0,206701	0,704317	−0,2935	−0,0346691
Foreignere_Instit	1,28393	0,438383	2,929	0,257150
DUndergrad_1	−0,153260	0,806745	−0,1900	−0,0262925
DUndergrad_2	0,837124	0,579365	1,445	0,155499
DUndergrad_3	0,436007	0,989374	0,4407	0,0845765
DUndergrad_4	0,310538	0,674675	0,4603	0,0574927
DExpertise_1	18,4350	19807,3	0,0009307	0,999483
DExpertise_2	19,6353	19807,3	0,0009913	0,997666
DExpertise_3	18,6382	19807,3	0,0009410	0,994481

Média var. dependente 0,308057 D.P. var. dependente 0,462788
R-quadrado de McFadden 0,349506 R-quadrado ajustado 0,234387
Log da verossimilhança −84,75963 Critério de Akaike 199,5193
Critério de Schwarz 249,7971 Critério Hannan-Quinn 219,8426

Número de casos 'corretamente previstos' = 170 (80,6%)
f(beta'x) na média das variáveis independentes = 0,176
Teste de razão de verossimilhança: Qui-quadrado(14) = 91,0814 [0,0000]

		Previsto	
		0	1
Efetivo	0	133	13
	1	28	37

Excluindo a constante, a variável com maior p-valor foi 21 (DExpertise_1)

Appendix 3 – Quality of the papers' journal

success	Paper	journal	SJR 2020	Q
exit	Fuller AW, Rothaermel FT (2012)	Strategic Entrepreneurship Journal	5,06	Q1
exit	Achleitner A, Braun R, Lutz E, Reiner U (2014)	Small Business Economics	2,2	Q1
exit	Jan-Georg Streletzki & Reinhard Schulte (2013)	Venture Capital	0,8	Q1
exit	Streletzki J, Schulte R (2013)	Journal of Small Business and Entrepreneurship	0,42	Q2
exit	Bellavitis, C., Filatotchev, I. and Kamuriwo, D. S. (2014)	Managerial and Decision Economics	0,29	Q3
exit	Rea, R. H. (1989).	Journal of business venturing	12.06	Q1
exits and amount of fund raised	Milosevic, Miona (2018)	Research Policy	3,67	Q1
funding amount	Walske, J. M., & Zacharakis, A. (2009).	Entrepreneurship Theory and Practice	5,37	Q1
funding amount	Cai, Zhang & Han (2020).	China Finance Review International	0,55	Q2
funding amount	Prohorovs, Bistrova, & Ten (2019).	Journal of East-West Business	0,27	Q3
IPO	Gompers, Paul A.; Mukharlyamov, Vladimir; Xuan, Yuhai (2016)	Journal of Financial Economics	11,67	Q1
IPO	Cumming, Douglas; Johan, Sofia (2016).	The Journal of Technology Transfer	5,78	Q1
IPO	Cyr LA, Johnson DE, Welbourne TM (2000)	Entrepreneurship Theory and Practice	5,37	Q1
IPO	Pan, F., Zhao, S. X., & Wójcik, D. (2016)	Geoforum	3,9	Q1
IPO	Henry Chen; Paul Gompers; Anna Kovner; Josh Lerner (2010)	Journal of Urban Economics	3,89	Q1
IPO	Boissin R, Sentis P (2014)	The European Journal of Finance	1,74	Q1
IPO	Hong, Suting; Serfes, Konstantinos; Thiele, Veikko (2020)	Journal of Economics & Management Strategy	1,67	Q1
IPO	Subhash KB (2003).	Journal of Social Sciences	-	-
other	Echols, A., & Tsai, W. (2005)	Strategic Management Journal	11,04	Q1

other	Jennifer M. Walske; Andrew Zacharakis (2009)	Entrepreneurship Theory and Practice	5,37	Q1
other	Cyr LA, Johnson DE, Welbourne TM (2000)	Entrepreneurship Theory and Practice	5,37	Q1
other	Zhang, Jing; Yu, Huizhi (2016)	Entrepreneurship Theory and Practice	5,37	Q1
other	Forti, Enrico; Munari, Federico; Zhang, Chunxiang (2019)	Strategic Entrepreneurship Journal	5,06	Q1
other	Rasmussen, Casper Claudi; Ladegård, Gro; Korhonen-Sande, Silja (2018)	Journal of Small Business Management	1,68	Q1
other	Schefczyk, M. (2001)	INFORMS Journal on Applied Analytics	1,63	Q1
other	Engel (2004)	Industry & Innovation	1,44	Q1
other	Dashti & Schwartz (2018)	Innovation	0,53	Q2
other	Huang, G. L., Hsu, H. L., & Cheng, W. S. (2010).	International Journal of Electronics & Communications	3.18	Q2
other	Sambasivan, Murali; Li-Yen, Lim; Che-Rose, Raduan; Abdul, Mohani (2010)	Journal of Small Business & Entrepreneurship	0,42	Q2
profit	Inkon, K. (2019)	Academy of Entrepreneurship Journal	0,21	Q3
profit	Witt, P. (2004).	Entrepreneurship & Regional Development	1,67	Q1
self-developed	Tinkler, Justine E.; Bunker Whittington, Kjersten; Ku, Manwai C.; Davies, Andrea Rees (2015)	Social Science Research	2,32	Q1
self-developed	West & Noel (2009)	Journal of Small Business Management	1,68	Q1
self-developed	Harrison, Richard T.; Mason, Colin; Smith, Donald (2015)	Entrepreneurship & Regional Development	1,67	Q1
self-developed	Kessler, Alexander (2007)	Entrepreneurship & Regional Development	1,67	Q1
self-developed	Kessler, Alexander (2007)	Entrepreneurship and Regional Development	1,67	Q1
self-developed	Sapienza, H., & Amason, A. (1993)	Interfaces	0,66	Q2
self-developed	Jan-Georg Streletzki & Reinhard Schulte (2013)	Journal of Small Business & Entrepreneurship	0,42	Q2
self-developed	Weber, C., & Weber, B. (2010)	International Studies of Management and Organization	0,41	Q2
self-developed	Kuckertz, Andreas; Kohtamaki, Marko; Korber, Cornelia Droege gen. (2010)	International Journal of Technology Management	0,37	Q2

self-developed	Martin, Mabunda Baluku; Julius, Fred Kikooma; Grace, Milly Kibanja (2016)	South African Journal of Business Management	0,18	Q4
survivability	Kerr, William R.; Lerner, Josh; Schoar, Antoinette (2014)	Review of Financial Studies	12,8	Q1
survivability	Bates T, Bradford WD. (1992)	Journal of Small Business Finance	4,54	Q1
survivability	Clarysse, Bobelyn, & del Palacio Aguirre (2013)	Small Business Economics	2,2	Q1
survivability	Brau JC, Brown RA, Osteryoung JS. (2004)	Journal of Small Business Management	1,68	Q1
survivability	Engel, D. (2004).	Industry & Innovation	1,44	Q1
survivability	Gerpott, Torsten J.; Niegel, Christian (2002).	International Journal on Media Management	0,56	Q2
survivability	Ehrensperger E, Erkhova D, Yadavalli A, Krohmer H. (2020)	Journal of Research in Marketing and Entrepreneurship	0,5	Q2
survivability	Abdou and Varela (2009)	Applied Financial Economics	0,48	Q1
survivability	Prohorovs, Bistrova & Ten (2018)	Journal of East-West Business	0,27	Q3
self-developed	Baluku, Kikooma and Kibanja (2016)	Journal of Small Business & Entrepreneurship	0,42	Q2
survivability	Roure, J. B., & Maidique, M. A. (1986).	Journal of business Venturing	12.06	Q1

Appendix 4 – Title of the papers referenced

Table 1: Title of the papers analyzed and their references (ref) (appendix)

Author, year and title of the paper
West, G. P., & Noel, T. W. (2009). The impact of knowledge resources on new venture performance. *Journal of Small Business Management*, *47*(1), 1-22.
Prohorovs, A., Bistrova, J., & Ten, D. (2019). Startup Success Factors in the Capital Attraction Stage: Founders' Perspective. *Journal of East-West Business*, *25*(1), 26-51.
Clarysse, B., Bobelyn, A., & del Palacio Aguirre, I. (2013). Learning from own and others' previous experience: the contribution of the venture capital firm to the likelihood of a portfolio company's trade sale. *Small Business Economics*, *40*(3), 575-590.
Cai, Z., Zhang, P., & Han, X. (2020). The inverted U-shaped relationship between crowdfunding success and reward options and the moderating effect of price differentiation. *China Finance Review International*.
Baluku, M. M., Kikooma, J. F., & Kibanja, G. M. (2016). Does personality of owners of micro enterprises matter for the relationship between startup capital and entrepreneurial success?. *African Journal of Business Management*, *10*(1), 13-23.
Tinkler, J. E., Whittington, K. B., Ku, M. C., & Davies, A. R. (2015). Gender and venture capital decision-making: The effects of technical background and social capital on entrepreneurial evaluations. *Social Science Research*, *51*, 1-16.
Walske, J. M., & Zacharakis, A. (2009). Genetically engineered: Why some venture capital firms are more successful than others. *Entrepreneurship Theory and Practice*, *33*(1), 297-318.
Streletzki, J. G., & Schulte, R. (2013). Which venture capital selection criteria distinguish high-flyer investments?. *Venture Capital*, *15*(1), 29-52.
Kessler, A. (2007). Success factors for new businesses in Austria and the Czech Republic. *Entrepreneurship and Regional Development*, *19*(5), 381-403.
Prohorovs, A., Bistrova, J., & Ten, D. (2019). Startup Success Factors in the Capital Attraction Stage: Founders' Perspective. *Journal of East-West Business*, *25*(1), 26-51.
Abdou, K., & Varela, O. (2009). Is there a puzzle in the failure of venture capital backed portfolio companies?. *Applied Financial Economics*, *19*(18), 1439-1452.
Dashti, Y., & Schwartz, D. (2018). Should start-ups embrace a strategic approach toward integrating foreign stakeholders into their network? *Innovation*, *20*(2), 164-191.
Echols, A., & Tsai, W. (2005). Niche and performance: the moderating role of network embeddedness. *Strategic Management Journal*, *26*(3), 219-238.
Ehrensperger, E., Erkhova, D., Yadavalli, A., & Krohmer, H. (2020). What really matters for startups in luxury: entrepreneurial luxury excellence. *Journal of Research in Marketing and Entrepreneurship*.
Gerpott, T. J., & Niegel, C. (2002). Mobile business start-ups in Germany: An exploration of the start-up scene and of corporate venture capital firms' views on business success drivers and inhibitors. *International Journal on Media Management*, *4*(4), 235-247.
Harrison, R. T., Mason, C., & Smith, D. (2015). Heuristics, learning and the business angel investment decision-making process. *Entrepreneurship & Regional Development*, *27*(9-10), 527-554.
Rasmussen, C. C., Ladegård, G., & Korhonen-Sande, S. (2018). Growth intentions and board composition in high-growth firms. *Journal of Small Business Management*, *56*(4), 601-617.
Sapienza, H. J., & Amason, A. C. (1993). Effects of innovativeness and venture stage on venture capitalist-entrepreneur relations. *Interfaces*, *23*(6), 38-51.
Schefczyk, M. (2001). Determinants of success of German venture capital investments. *Interfaces*, *31*(5), 43-61.
Streletzki, J. G., & Schulte, R. (2013). Start-up teams and venture capital exit performance in Germany: venture capital firms are not selecting on the right criteria. *Journal of Small Business &*

Entrepreneurship, *26*(6), 601-622.
Pan, F., Zhao, S. X., & Wójcik, D. (2016). The rise of venture capital centres in China: A spatial and network analysis. *Geoforum*, *75*, 148-158.
Weber, C., & Weber, B. (2010). Social capital and knowledge relatedness as promoters of organizational performance: An explorative study of corporate venture capital activity. *International Studies of Management & Organization*, *40*(3), 23-49.
Walske, J. M., & Zacharakis, A. (2009). Genetically engineered: Why some venture capital firms are more successful than others. *Entrepreneurship Theory and Practice*, *33*(1), 297-318.
Kerr, W. R., Lerner, J., & Schoar, A. (2014). The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, *27*(1), 20-55.
Klein, J., Stuckenborg, L., & Leker, J. (2020). Hot or not–Which features make FinTechs attractive for investors?. *The Journal of Entrepreneurial Finance*, *22*(1), 1.
Achleitner, A. K., Braun, R., Lutz, E., & Reiner, U. (2014). Industry relatedness in trade sales and venture capital investment returns. *Small Business Economics*, *43*(3), 621-637.
Bates, T., & Bradford, W. D. (1992). Factors affecting new firm success and their use in venture capital financing. *The Journal of Entrepreneurial Finance*, *2*(1), 23-38.
Bellavitis, C., Filatotchev, I., & Kamuriwo, D. S. (2014). The effects of intra-industry and extra-industry networks on performance: A case of venture capital portfolio firms. *Managerial and Decision Economics*, *35*(2), 129-144.
Boissin, R., & Sentis, P. (2014). Long-run performance of IPOs and the role of financial analysts: some French evidence. *The European Journal of Finance*, *20*(2), 125-149.
Brau, J. C., Brown, R. A., & Osteryoung, J. S. (2004). Do venture capitalists add value to small manufacturing firms? An empirical analysis of venture and nonventure capital-backed initial public offerings. *Journal of Small Business Management*, *42*(1), 78-92.
Chen, H., Gompers, P., Kovner, A., & Lerner, J. (2010). Buy local? The geography of venture capital. *Journal of Urban Economics*, *67*(1), 90-102.
Cumming, D., & Johan, S. (2016). Venture's economic impact in Australia. *The Journal of Technology Transfer*, *41*(1), 25-59.
Cyr, L. A., Johnson, D. E., & Welbourne, T. M. (2000). Human resources in initial public offering firms: do venture capitalists make a difference? *Entrepreneurship Theory and Practice*, *25*(1), 77-92.
Cyr, L. A., Johnson, D. E., & Welbourne, T. M. (2000). Human resources in initial public offering firms: do venture capitalists make a difference? *Entrepreneurship Theory and Practice*, *25*(1), 77-92.
Engel, D. (2004). The performance of venture-backed firms: the effect of venture capital company characteristics. *Industry and Innovation*, *11*(3), 249-263.
Forti, E., Munari, F., & Zhang, C. (2020). Does VC backing affect brand strategy in technology ventures? *Strategic Entrepreneurship Journal*, *14*(2), 265-286.
Fuller, A. W., & Rothaermel, F. T. (2012). When stars shine: The effects of faculty founders on new technology ventures. *Strategic Entrepreneurship Journal*, *6*(3), 220-235.
Gompers, P. A., Mukharlyamov, V., & Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, *119*(3), 626-644.
Sambasivan, M., Li-Yen, L., Che-Rose, R., & Abdul, M. (2010). Venture performance in Malaysia: Personal initiative, human capital, and competency areas of founding entrepreneurs as critical success factors. *Journal of Small Business & Entrepreneurship*, *23*(3), 315-332.
Zhang, J., & Yu, H. (2017). Venture capitalists' experience and foreign IPOs: evidence from China. *Entrepreneurship Theory and Practice*, *41*(5), 677-707.
Kuckertz, A., Kohtamäki, M., & Droege gen. Körber, C. (2010). The fast eat the slow–the impact of strategy and innovation timing on the success of technology-oriented ventures. *International Journal of Technology Management*, *52*(1/2), 175-188.
Hong, S., Serfes, K., & Thiele, V. (2020). Competition in the venture capital market and the success of

startup companies: Theory and evidence. *Journal of Economics & Management Strategy*, *29*(4), 741-791.
Inkon, K. (2019). A cross-sectional study on the relationship between business plan, entrepreneur type, development stage and profitability of US SMEs. *Academy of Entrepreneurship Journal*, *25*(1), 1-21.
Roure, J. B., & Maidique, M. A. (1986). Linking prefunding factors and high-technology venture success: An exploratory study. *Journal of Business Venturing*, *1*(3), 295-306.
Rea, R. H. (1989). Factors affecting success and failure of seed capital/start-up negotiations. *Journal of Business Venturing*, *4*(2), 149-158.
Subhash KB (2003). Venture capital - success factor for business ideas. *Artha: Journal of Social Sciences.* 2(1); 2003; 1-19.
Witt, P. (2004). Entrepreneurs' networks and the success of start-ups. *Entrepreneurship & Regional Development*, *16*(5), 391-412.
Huang, G. L., Hsu, H. L., & Cheng, W. S. (2010). The Key Factors to the Successful Generation of Intellectual Capital: The Bank Corporate Loans Department Example. *International Journal of Electronic Business Management*, *8*(2).
Milosevic, M. (2018). Skills or Networks? Success and Fundraising in a Low Performing Venture Capital Market. In *Academy of Management Proceedings* (Vol. 2017, No. 1, p. 13365).
Santisteban, J., & Mauricio, D. (2017). Systematic literature review of critical success factors of information technology startups. *Academy of Entrepreneurship Journal*, *23*(2), 1-23.

Source: created by the authors, based on our sample's data.