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Technology and financial markets: venture capital perspectives

By

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Declaration

I hereby declare that the contents and organization of this dissertation constitute my own original work and does not compromise in any way the rights of third parties, including those relating to the security of personal data.

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2023

*This dissertation is presented in partial fulfillment of the requirements for **Ph.D. degree** in the Graduate School of Politecnico di Torino (ScuDo).

I would like to dedicate this Thesis to my family: my wife Sara, my mum Speranza, my dad Roberto, my brother Fabrizio, his wife Elena, my grandparents Augusta and Salvatore, and my lovely nephews Federico, Vittoria, and Ludovica – they are the supporting pillars of my life.

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Abstract

This thesis deals with the fascinating world of Venture Capital, where, daily, investment professionals bet on high-risk, high-reward ventures with the potential to change the way we all live radically. As the phenomenon has reached a global scale and magnitude, with more than $600 billion invested in 2021, it has become particularly relevant to investigate whether this capital is used efficiently and wisely. To this end, this work contributes to two research streams. Firstly, it explores the social impact investment phenomenon by analyzing a proprietary dataset of more than 60 funds and 300 companies associated with the relative financial and accounting information. It describes the dynamics of this growing trend and the economic impact of such investments on the backed companies, finding a positive effect in the medium and long term. By doing so, it tries to address a growing concern on whether and to what extent investment professionals care about the social impact of their activity. Secondly, it analyzes the ability of VCs to select promising technologies. To this end, two methodologies are used. On the one hand, building on the findings of a Delphi forecasting technique, the work compares the investment choices of venture capitalists to opinions gathered from industry experts on possible blockchain-enabled futures. Interestingly, VC investment choices fit the highest-risk scenarios depicted by industry experts, confirming the strong risk attitude of such investment professionals. On the other end, it exploits a novel and proprietary dataset including both listed and VC-backed companies active in the biotechnology and pharmaceutical industry to assess whether financial markets reward high-risk VC-backed technology more than traditional and more mature solutions. Interestingly, but not surprisingly, the opposite

seems to hold true, as financially-driven markets struggle to value high-risk technology that can only provide financial returns in the long run.

This research confirms the need for venture capitalists in the innovation ecosystem and confirms an optimistic view about the future. VCs, who have the honor and burden of selecting, working, and nurturing the innovators of tomorrow, are starting to care about the social impact of their investment and, coherently with their nature, are betting on the most disruptive technologies, the ones that none else would be that fool to support, but that could radically change our lives (for the better).

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Chapter 1

Venture Capital in a nutshell

Since the early 1900s, people with good ideas (often inventors) looked for people with money (i.e., investors) to provide them with the capital to develop and commercialize their inventions. At the same time, wealthy families and individuals looking for original ways to increase their wealth started betting on high-risk, high-reward technological projects with the potential to disrupt and improve how people live. A few decades after, in 1946, in the United States, the venture capital (VC) phenomenon officially kicked off with the birth of the first "modern" VC firm, the American Research & Development Corporation (ARD). Since then, the industry has heavily changed and evolved until it assumed the peculiar characteristics, dynamics, and global presence of these recent days. Over the years, and coherently with the risk profile of the asset class, the VC phenomenon has led to tremendous breakthroughs (and financial returns) in various fields (leading, for example, to the commercialization of insulin for human use), but also to loud failures (it is sufficient to think about the Theranos scandal which hit the headlines various times in the past decade[1]).

[1] Business Insider (2018)

Before digging more specifically into the questions this work will address, it is interesting to have a first look at where the VC industry stands today globally. Over the recent years, the sector has increasingly gained relevance, growing to more than $600 billion invested globally in 2021, soaring from $335 billion in 2020[2]. Although the phenomenon has now reached a global presence, it is still predominantly US based. In 2021, more than $300 billion of investments (approximately 50% of the total global volume) were deployed in the United States, with the Asia region following at $176 billion[3]. This massive deployment of capital, which doubled from 2020, was associated, although not precisely proportionally, with a record-high number of unicorns (i.e., privately held companies valued at $1 billion or more). While at the end of 2020, the number of unicorns was just surpassing the 500 mark, 2021 saw the creation (net of the companies which lost their unicorn status) of 390 new super start-ups, making it one of the most favorable years for the start-up ecosystem since VC inception in 1946. While these figures could suggest the entrepreneurial ecosystem is witnessing incredible growth, the whole picture must be contextualized by looking at the global macroeconomic scenario. As Gompers et al. (2008) stressed, the VC market is tightly correlated to macroeconomic conditions affecting public equity markets. From this perspective, 2021 was remarkably associated with inflationary conditions due to the monetary policies that central banks put in place to stimulate economies after the COVID-19 pandemic shock, the Russo-Ukrainian war, and the heavy disruptions in global supply chains. Dealing with the drivers and impact of the macroeconomic scenario on the VC market is definitely outside the scope of this work. It could easily constitute ad-hoc research, but it is definitely helpful for the interpretation of the sky-rocketing figures that we all witnessed in the past couple of years.

[2] Crunchbase, 2021
[3] CbInsights Research, 2021

Over the years, the VC sector has been thoughtfully investigated by academics and practitioners with different backgrounds and looking at different dimensions. What makes the industry particularly appealing are its intrinsic and unique characteristics. In VC, small investment teams allocate huge amounts of money to innovative ventures and technologies, betting on different possible futures. Given the relevance (in terms of dimensions) of the assets that these teams manage (almost $2 trillion in assets under management in 2022[4]), those investment professionals, by selecting the companies in which they invest, are heavily influencing the technological development and direction of our society. Thus, the impact on our economy and society of such a small number of professionals is enormous (Gornall and Strebulaev, 2021), and financing the right innovations is key to successfully facing many of the challenges of our century (i.e., the climate one, access to food and water, raising inequality, etc.).

1.1 Two fundamental questions

The characteristics of the VC industry, briefly described in the previous section, have spurred the fundamental questions this work will try to address. Given that venture capitalists manage $2 trillion and have the mandate to invest this money in the technologies and services we will use in the future, two questions are highly relevant.

The first aim is to investigate whether and to what extent VCs play a relevant role in financing social impact ventures. Although the whole phenomenon has been born with a purely financial purpose (i.e., to provide above-the-average returns for investors by taking above-the-average risks), the social impact of such investments has gained exponentially increasing relevance given the extreme challenges our society faces in the modern days. Although highly relevant, the academic literature on the topic is still widely underdeveloped, and this work tries to contribute in a

[4] Preqin, 2022

structured way to this growing body of research. Thus, from one perspective this work aims at providing a first organic and comprehensive description of the social impact investing phenomenon. On the other side, it strives to evaluate the relevance of VC money on social impact ventures, not only from the financial side, but also looking at the capacity to spur growth.

Secondly, the focus of the work is to contribute to the understanding of the capabilities of VCs in selecting promising technologies. Aside from the social impact they have, it is interesting to understand if there is consensus among different actors (both industry experts and public equity markets) on the technologies selected and invested by venture capitalists. To this aim, the work will focus on two industries that have witnessed tremendous growth in terms of the investments received over the last few years: the blockchain and biotechnology sectors. Blockchain-based start-ups raised more than $30 billion[5], and biopharma's private investment soared to over $22 billion in 2021[6], accounting for more than 8% of the total invested capital for the year. The question arises spontaneously, are VCs using their (or better, the money of their investors) wisely?

The rest of this thesis is organized as follows to give the best possible answers to the questions mentioned above. Chapter 2 digs into the realms of social impact investing. In chapter 3, a forecasting technique has been used to analyze the outlook of blockchain technology, involving a heterogenous pool of experts and comparing experts' opinions with venture capitalists' investment choices. Chapter 4 evaluates the market value of VC-backed technologies in the biopharmaceutical sector, and eventually, Chapter 5 provides some final remarks.

[5] ETF Database, 2022
[6] Fierce Biotech, 2022

Chapter 2

The Social Impact of Venture Capital Investing

Note: the chapter includes material as published in the article: "Croce, A., Ughetto, E., Scellato, G., & Fontana, F. (2021). Social impact venture capital investing: an explorative study. Venture Capital, 23(4), 345-369."

2.1 Introduction

In recent years, social impact (henceforth, SI) investing has gained an exponentially increasing attention from many different actors across the globe. Financial institutions, private and public companies and shareholders have started to look at financial investments also through the lenses of the SI they generate (Fink 2018, 2020; Hart and Zingales 2017; Zingales 2018).

SI investments can be conceptualized as investments that strive to achieve a measurable social impact (i.e., social, economic, cultural or environmental) alongside a financial return, which can range from the repayment of the capital to a risk-adjusted market rate of return (Arena et al. 2018) . The market for SI investments is progressively growing: in its most recent survey, the Global Impact Investing Network (GIIN) has reported that in 2019 about 279 SI investors (mostly located in North America and Europe) financed 9,807 SI investments, worth a total of more than 46.8 billion dollars (GIIN 2020). In the next decades, it is reasonable to presume that a consistent amount of capital will be allocated to social enterprises (Lyons and Kickul 2013).

Among the heterogeneous pool of actors that constitute the SI investing realm, Social impact venture capitalists (henceforth, SIVCs) are a new organizational form for which the tension between financial logic and social impact is most prominent. SIVCs operate with a hybrid logic (Battilana et al. 2017; Miller and Wesley II 2010), by combining financial sustainability with the generation of social value. They act as "pragmatic idealists" (Bocken 2015): on the one side, they evoke traditional VCs in their governance structures and general investment practices, but, on the other side, they look beyond a traditional 'quick-win investment format'. In fact, they deliberately invest in businesses that are economically viable, but also that are expected to generate economic, environmental, and social value.

SIVCs apply principles and practices borrowed from the VC industry (Cetindamar and Banu Ozkazanc-Pan 2017), but they differ from traditional VCs in that they aim at catalysing funding to tackle persistent domestic or global social problems. The creation of social value goes hand in hand with a more patient attitude and the generation of varying levels of financial returns, reflecting their different expectations regarding risk, return and impact. While many SIVCs are guided by a strong financial logic and target market-competitive financial returns from their SI investments (often named financial-first investors), others seek to maximize social or environmental returns, also at the potential detriment of financial returns (often named impact-first investors) (Ormiston et al. 2015).

Given the scenario in which SIVCs operate, where rules and practices are not well-established or known and because they are relatively new subjects in the venture capital (VC) market, research in this field has received very little attention. Thus far, a few works have focused on the blended value strategies that SIVCs adopt (Barber, Morse, and Yasuda 2021; Block, Hirschmann, and Fisch 2021; Boni, Toschi, and Fini 2021; Geczy et al. 2021; Toschi, Ughetto, and Fronzetti Colladon, 2021). No research we are aware of has attempted to provide a systematic overview of the SIVC market. Hence, the main aim of this research is to fill this gap and

provide an analysis of the trends and the main characteristics of the SIVC industry at international level. The paucity of academic work on SIVCs is in contrast with the early momentum that SI investment is witnessing. SI investments are receiving much attention from the financial press (Fink 2018, 2020; The Economist 2017; Zingales 2018), and this makes envisage a growing relevance of this form of VC financing in the near future.

In this chapter, we aim at analyzing the players within the VC landscape that are driven by impact generation. By definition, VC funds do not only select promising investments but provide strategic guidance to the invested companies as well. From this perspective, these impact-driven VC players have a double opportunity to achieve positive externalities: from one side, they can allocate capital to the most deserving companies, but, afterwards, they can provide operational and strategic competences to ensure that impact objectives are successfully achieved and maximized alongside financial returns.

We provide a detailed description of SIVCs in terms of their geographical location, target investment areas, investment size, target industries, investment stages and impact objectives. In doing so, we map the current global landscape of SIVCs. Additionally, we present a first evidence about the economic and financial status of the companies invested by SIVCs. We also assess the short-term and long-term impact of SIVCs on the performance of funded companies. Based on data retrieved from ImpactBase, an online database managed by the GIIN, we aim at describing the peculiarities of the SIVC phenomenon. Additionally, in order to better understand SIVCs' investment criteria, we complement the ImpactBase dataset with additional information on the invested companies, deriving data from Thomson One Banker dataset. Finally, in order to examine the characteristics of the ventures funded by SIVCs, we enrich the analysis with accounting data on the invested companies drawn from ORBIS dataset.

We believe that the picture we offer on the role played by SIVCs paves the way to better understand and structure the complex, multi-faced and evolving SI landscape, which could lead to the creation of a new segment of financial operators with consistent capital under management looking for double bottom line returns, i.e., financial and not-pecuniary ones. By illustrating the peculiarities and main features of the SIVC market, this work enlarges the information set available to policymakers, at both national and supranational levels, to improve entrepreneurial finance policies.

The rest of the chapter is organized as follows. Section 2 provides a discussion on how to define SI investing and a review of the current literature. Section 3 describes the dataset and introduces some insightful descriptive statistics about SIVCs and their funded companies. In section 4, we measure the short-term and long-term impacts of SIVCs on the performance of funded companies. Section 5 concludes the work.

2.2 Theoretical Background

2.2.1 Defining SI investing

As previously highlighted, the scientific literature related to SI investing appears to be still underdeveloped. While the practitioner world runs fast, from an academic perspective, the research is still very much in its infancy (Nicholls and Daggers 2016). This paucity of studies is also linked to the confusion on the proper definition and the related boundaries of the SI investing phenomenon (Klingler-Vidra 2020) . Thus, it appears of primary importance to provide a comprehensive definition of what is meant by SI investing. As highlighted by Berry and Junkus (2013), and found by studies run by JP Morgan and GIIN, many investors do not agree upon a shared vision of what the term actually means and which kind of financial activities it includes. Given the ambiguity and uncertainty surrounding the term “impact”, an investment can easily be considered impactful (even if it is not),

allowing financial actors to use the label of impact investor merely to exploit the momentum without generating concrete impact for the society (Findlay et al. 2019; Freireich et al. 2009). Thus, most of the available studies have tried to give precise boundaries to the phenomenon, coming up with different definitions.

According to a broader definition, SI investing is an investment process that integrates social, environmental, and ethical considerations into investment decision making. Indeed, what differentiates a SI investment from standard investments is the introduction of SI factors into the investment process. This means that whatever investment seeking to achieve a positive impact on society should be considered as SI investment, e.g. running from philanthropic to responsible and sustainable investments (Berry and Junkus 2013; Scarlata, Walske, and Zacharakis 2017; Schueth 2003; Shank, Manullang, and Hill 2005; Statman 2006), with the inherent risk of diluting the concept (the so-called "impact washing" (Harji and Jackson 2012)).

Recently, more stringent characteristics have been proposed to classify investments as SI ones. SI investing occurs any time there is a deliberate decision to achieve both a financial return and an ancillary social and/or environmental benefit from the investment opportunity (Barber, Morse, and Yasuda 2021; Hebb 2013). Accordingly, GIIN defines impact investing as "investments made with the intention to generate positive, measurable social and environmental impact alongside a financial return" . This definition implies two other fundamental components: first, the intent of the investor to achieve such impacts, and, second, tangible evidence of the impacts themselves (Jackson 2013). As highlighted by Weber (2006) and Buttle (2007), the final goal for SI investors is in fact to allocate capital in businesses that have the intention to produce socially and environmentally sustainable impacts but that, at the same time, offer an economic and financial return as well. In contrast to this approach, conventional financial investment activity only seeks financial returns (Geobey, Westley, and Weber 2012).

To date, there is still an open debate in the literature regarding the magnitude of the financial returns that could be allowed for SI investments. Some works do not foresee boundaries on financial returns, while others are favourable to consider as SI investments only the ones which are available to sacrifice financial returns in favour of social returns (e.g., when below risk-adjusted market return rates are to be expected) (Arena et al. 2018). Höchstädter and Scheck (2015) argue that impact has to be measurable and intentional to differentiate it from unintentional positive externalities that could be generated by any investment. Another qualifying element to define impact investing, in addition to intentionality and measurability, is additionality (Bugg-Levine and Emerson 2011; Hebb 2013; O'Donohoe et al. 2010; So and Staskevicius 2015).

2.2.2 The literature

The proliferation of investors pursuing blended value strategies (i.e., targeting both economic and social returns) has recently led to the explosion of works on socially responsible investments (SRI). This broad literature has discussed the increasing awareness of investors to social, environmental, and ethical issues (Barreda-Tarrazona, Matallín-Sáez, and Balaguer-Franch 2011; Berry and Junkus 2013; Erhemjamts, Li, and Venkateswaran 2013; Nilsson 2008; Sandberg et al. 2009). However, according to the review by Renneboog, Ter Horst, and Zhang (2008), existing studies have not univocally demonstrated that SRI investors may be willing to accept suboptimal financial returns in order to pursue social or moral goals. SIVCs, which are emerging in this new and evolving landscape as new actors, have received very little attention from the literature. A few scientific contributions are provided in the area of sustainable VCs (De Lange and Valliere 2020), for example those funds operating in the cleantech field (Bocken 2015; Marcus, Malen, and Ellis 2013; Wüstenhagen and Teppo 2006). Other works have examined the market and performance of community development VCs in the US, finding that these funds tend to invest in lagging regions, in earlier-stage

investments and in industries that are not usually covered by traditional VCs and are less likely to result in successful exits (Kovner and Lerner 2015).

Only recently, a scientific debate on this new organizational form has emerged (Barber, Morse, and Yasuda 2021; Block, Hirschmann, and Fisch 2021; Boni, Toschi, and Fini 2021; Geczy et al. 2021; Toschi, Ughetto, and Fronzetti Colladon, 2021). The first one is the study by Barber, Morse, and Yasuda (2021), which examines whether investors knowingly accept lower expected financial returns in exchange for nonpecuniary benefits from investing in SIVCs. They find that investors are willing to pay for impact by sacrificing returns, being this result robust to fund access rationing and investor heterogeneity. Block, Hirschmann, and Fisch (2021) apply an experimental conjoint analysis to examine the impact investor criteria when screening social enterprises. They find that equity investors convey a greater value on the large-scale implementation of the social project compared to other social impact investors (such as donors or debt investors). Boni, Toschi, and Fini (2021) examine the relationship between investors' aspirations toward social impact and portfolio firms' pursue of social goals. Results reveal the existence of an investor–portfolio alignment effect in blended value strategies and this effect is influenced by contingencies at both investor and portfolio levels. Geczy et al. (2021) analyse legal documents from SIVCs and show that these contracts assign rights and duties on the basis of impact (what is termed "operational impact") and provide specific impact goals, indicating the intention that investors have to seek and deliver impact (what is termed "aspirational impact"). Similar to the field of social entrepreneurship, where the emphasis on generating rents or promoting a social mission may vary (Dees and Elias, 1998), also in the SIVC context investors' focus on the social dimension-rather than on the financial one- may vary. This issue is examined by Toschi, Ughetto and Fronzetti Colladon, (2021) who explore how SIVCs communicate their identities and actions to their external stakeholders. Through the use of text mining techniques they find differences among SIVCs in

terms of the intensity they communicate the social impact theme and the distinctiveness of the language used.

2.3 Dataset and descriptive statistics

2.3.1 Dataset description

This section describes how data were collected to build the database of SIVCs. The primary source of data is ImpactBase, an online database owned by GIIN, which is dedicated to the SI investment industry.

The dataset includes information on 443 active funds till December 2018. Out of these 443 active funds, we filtered only the ones belonging to the "venture capital" asset class, which constitute the body of our research, leading to an initial sample of 275 SIVCs. The database provides descriptive information of the funds – such as location, target geographical investment area and corporate governance. However, only for 92 SIVCs (out of 275) the set of information was complete. In Section 3.2 we provide a first set of descriptive statistics on these 92 SIVCs.

To enrich the dataset with quantitative data, we complemented the information drawn from ImpactBase with a second database, namely Thomson One Banker, owned by the Thomson Reuters group. This database is one of the largest and most complete sources of financial information in the world, with a coverage comparable to Bloomberg LP and FactSet Research Systems Inc. From this second dataset, we derived information about the companies invested by SIVCs and the characteristics of the funding rounds. We found information in Thomson One Banker for 65 SIVCs (out of the original 92), 322 funded firms and 455 deals. A second set of descriptive statistics is carried out in Section 3.2 on this enriched dataset.

Finally, we focus on the invested companies by SIVCs. To this aim, the database ORBIS, managed by Bureau van Dijk, has been merged with the one previously used. This dataset contains accounting data for the majority of the

European companies, and for some companies located in other countries. After the merge, we have complete financial accounting data on 51 (out of the total 322) social enterprises funded by a subset of 22 SIVCs (out of the 65 previously mentioned). For these 51 companies, we have been able to observe accounting data (even though not for all the variables included in the analysis) relative to the year in which they received the investment, as well as for some years before and some years after the round itself. The total number of observations is 302 (5.912 observation, on average, per company). Figure 1 illustrates the dataset construction process as described.

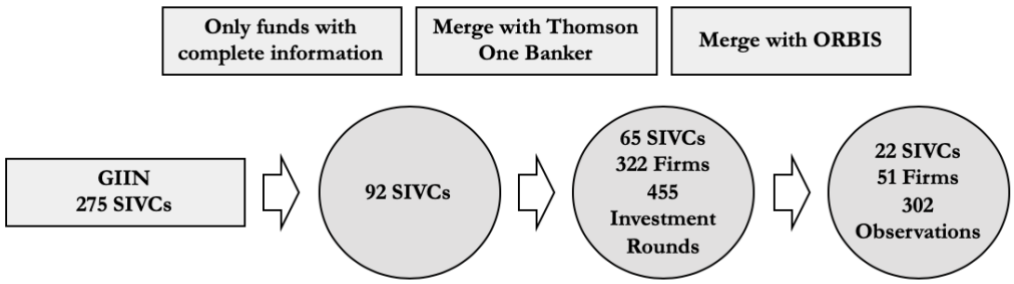


Figure 1 - Dataset construction process

2.3.2 A sketch on the SIVCs' market

The main aim of this work is to describe the phenomenon of SIVC investing. As said in the previous section, we first focus on the 92 SIVCs extracted from ImpactBase, for which we have been able to collect complete information. Out of these 92 funds, 17 (18.48%) are closed, while the others are still operating. We observe a heterogenous behaviour in terms of investment activity, measured as the number of investments made at the time of writing, as detailed in Table 1. As it can be noticed, and in line with the novelty of the phenomenon, 20 funds (21.74%) have not yet completed the first investment. Most of the funds has successfully invested

in less than 15 companies, while the 16.32% of the sample has made more than 15 investments.

N. Investments	N. SIVCs	%
0	20	21.74%
1-5	22	23.91%
6-10	18	19.56%
11-15	17	18.48%
>15	15	16.32%
Total	*92*	*100,00%*

Table 1 - SIVCs' investment activity

To gain a better understanding of the geographic distribution of SIVCs worldwide, and of their target investment areas, we report, in Figure 2, two maps that visually show where SIVCs are headquartered, and which are their target investment areas. We observe that, not surprisingly, and in line with the VC phenomenon, North America (US and Canada) is the most active region with 47 funds out of the total 92 (51.65%). Europe (23.08%) and Africa (16.48%) follow, thanks to the presence of fiscal paradises (e.g., Guernsey, Mauritius, Luxembourg, Cayman Islands). The remaining 5.49% and 3.3% are relative to Asian and South American funds, respectively.

Focusing on the continent of target investments, North America appears to be the most common target investment area with 37% of the funds indicating it as a target investment area, followed by Asia (30%), Africa (18%), Europe and South America (15%).

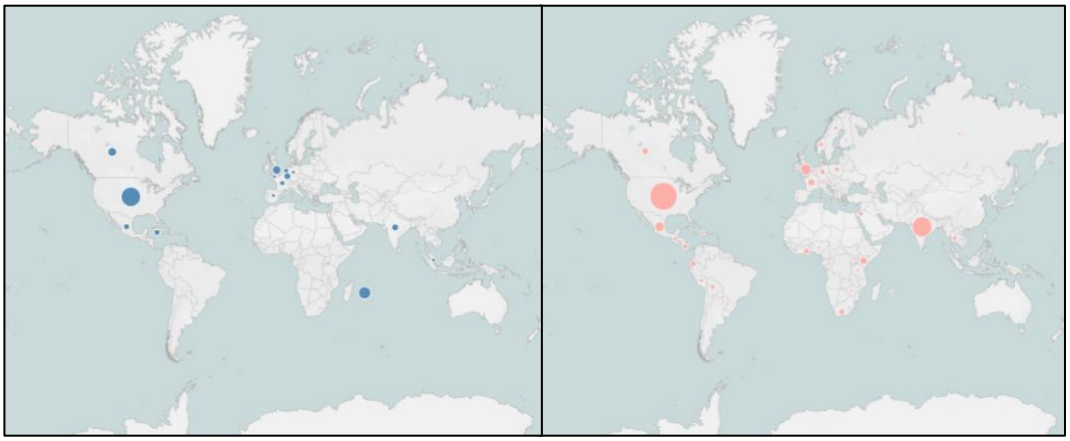


Figure 2 - Geographic distribution of SIVCs and invested companies

It is also interesting to examine if and to what extent SIVCs aim to invest cross-border. In Table 2, we show the target investment countries and the continent of incorporation of the funds. Results show that SIVCs prefer to invest locally (i.e., in the same continent in which the registered office of the fund is located). Asian SIVCs invest only in Asian companies, African SIVCs focus 53% of their investments in African companies, while 56% of North American investments are targeted in North America. Similarly, 60% of South American companies are invested by South American funds. Only European SIVCs show a more spread target investment activity, with a comparably lower 40% of their investments in European companies, while the remaining investments are uniformly distributed across Africa (20%), Asia (20%) and South America (16%). Moreover, there is no evidence of non-North American funds indicating North America as target investment area. This fact seems to indicate that being based in North America is the only way to access the start-up market in this area.

Continent of SIVCs	**Target Investment Area**						
	Africa	Asia	Europe	North America	Central America	South America	***Total***
Africa	47%	53%	0%	0%	0%	0%	100%
Asia	0%	100%	0%	0%	0%	0%	100%
Europe	20%	20%	40%	0%	4%	16%	100%
North America	7%	13%	7%	56%	8%	10%	100%
South America	0%	0%	0%	0%	40%	60%	100%

Table 2 - SIVCs' investment dynamics: cross continent investments

When we focus on the performance of SIVCs, interestingly, 85 out of 92 declare to have, as a goal, a return comparable to the market one, independently of being SIVCs. Only 7 funds appear to be willing to sacrifice financial success with impact. This consideration is particularly relevant as it clashes with the definition provided before. Indeed, the intentionality of sacrificing financial returns in favour of impact appears to be foundational for the SI investing phenomenon. Management fees are also in line with the traditional VC industry, with most of the funds (59.78%) requiring fees between 2% and 3%.

In Table 3 we compare the target internal rate of return (IRR)- that each fund strives to achieve- and the committed capital of SIVCs. We find out that globally, the mean value of the target IRR is 19% (median value 18.14%) and that the mean value of the committed capital is 60.73 M$ (median value 29.1M$).

	Committed Capital (M$)		Target IRR (%)	
	Mean	Median	Mean	Median
Total sample	*60.73*	29.1	19	18.14

Table 3 - IRR and committed capital of SIVCs

Table 4 illustrates the different typologies of limited partners investing in SIVCs. Family Office (78%) and Institutional Investors (71%) represent the most used sources of capital for these socially responsible financial vehicles, followed by Pension Funds (41%) and Endowments/Foundations (40%).

Limited Partner Type	% of total sample
Development Finance Institution	39%
Pension Fund	41%
Retail Investors	13%
Family Office	78%
Other Institutional Investors	71%
Endowments/Foundations	40%
Individual Accredited Investor	8%

Table 4 - Percentage distribution of Limited Partners of SIVCs

As the recent literature has highlighted, SIVCs reflect their impact agenda in legal documents, by providing their intention to seek and deliver impact (Geczy et al 2021). The impact agenda of SIVCs may be broad, ranging from funds that seek to improve the access of poor people to microfinance, reduce the environmental

impact of gas emissions, alleviate poverty or encourage the development of entrepreneurial firms by minority communities. The GIIN codified the impact agenda of SIVCs in different categories, reflecting societal areas potentially affected by SI investments. SIVCs indicated more than one impact theme that they intended to address by the allocation of their capital. Therefore, the impact theme reflects the area in which the recipients of the funds are operating. To clarify, a SIVC willing to have a positive impact on facilitating the access to water of underdeveloped countries will invest in companies whose mission is to develop technologies or services which eventually improve people's access to water. The same reasoning applies to the other impact themes that are presented in Table 5. We aggregated the categories provided by the GIIN into macro-level themes. We classified the impact themes as follows: "Basic Services", referring to companies improving people's access to food, water and education, "Employment" referring to companies which try to improve the life of jobseekers, "Energy and Environment", related to the striking global challenge for contrasting climate change, and "Finance", which mainly refers to companies improving people's access to microcredit.

We find out that most of examined SIVCs are interested in social enterprises striving to provide access to Basic Services (i.e., food, water, education), since 58.69% have indicated Basic Services as one of the impact themes driving their investment choices. Other priority impact themes are Employment (53.26%), Energy and Environment (53.26%) and Finance (51.08%).

	Social Impact Theme			
	Basic Services	Employment	Energy and Environment	Finance
% of funds	58.69 %	53.26%	53.26%	51.08%

Table 5 - Social Impact themes

As previously stated, to get additional insights on the phenomenon in terms of data on invested companies, we merged Thomson One Banker information with the initial database, leading to complete information for 65 funds investing into 322 companies in 455 deals. The distribution of the deals over time is reported in Table 6. Results highlight the novelty of the SIVC investing phenomenon: only 14.96% of the investments are made before 2005, 25.27% are made from 2006 to 2010, 42.19% from 2011 to 2015 and 17.58% after 2016.

Years	N. investments	%
Before 2000	12	2.64%
2001-2005	56	12.32%
2006-2010	115	25.27%
2011-2015	192	42.19%
2016-2018	80	17.58%
Total	*455*	*100,00%*

Table 6 - Distribution of SIVC investments over time

Table 7 reports the distribution of the companies invested by SIVCs by country, industry, status, and stage. We observe that, in line with the target investment geographical areas stated by the funds and described in Figure 2, North America appears to be the area receiving most of the investments. Indeed, 52.80% of 322 invested companies are from North America, 21.74% are from Asia and 14.60% are from Europe. African companies represent the 7.45% of the invested companies, while the remaining 3.42% come from South America.

As to the industrial distribution, the higher percentage of companies (30.43%) operates in the "Other" sectors category that includes "Agriculture related" (NACE

Code 9510) and “Non-Bank Credit” (NACE Code 9235) sub-sectors. Similarly, 48 companies (14.91% of the sample) operate in the Industrial Energy sector. However, we also find “standard” sectors for VC investing such as “Internet Specific” (18.32%) and “Computer Software” (12.73%) sectors.

As to the status of the invested companies, the largest majority is still active (78.88%). Descriptive statistics reveal that 19.57% of the companies went into a successful exit trough an M&A (15.53%) or an IPO (4.04%). Only 1.55% of the invested companies failed. This result, even if it is influenced by the fact that most of the investments is recent, provides a first insight about the positive effect of SIVC investing.

Table 7 also reports the distribution of the invested companies by stage of development. The numbers suggest that SIVCs, in accordance with traditional VC funds, are mostly focused on the growth stage (45.03% of the companies), followed by the early and seed stages (28.88% and 2.8% of the companies respectively). The remaining 23.29% of the investments are in later stage companies.

Company Country	**Total**	**%**
Africa	24	7.45%
Asia	70	21.74%
Europe	47	14.60%
North America	170	52.80%
South America	11	3.42%
Total	*322*	*100%*
Company Industry	**Total**	**%**

Biotechnology	7	2.17%
Communications	11	3.42%
Computer Hardware	1	0.31%
Computer Software	41	12.73%
Consumer Related	33	10.25%
Industrial Energy	48	14.91%
Internet Specific	59	18.32%
Medical Health	16	4.97%
Other	98	30.43%
Semiconductor Electronics	8	2.48%
Total	*322*	*100%*
Company Status	**Total**	**%**
Active	254	78.88%
Failed	5	1.55%
M&A	50	15.53%
IPO	13	4.04%
Total	*322*	*100%*
Company Stage	**Total**	**%**

Seed stage	9	2.80%
Early stage	93	28.88%
Growth stage	145	45.03%
Later stage	75	23.29%
Total	*322*	*100%*

Table 7 - Distribution of invested companies: country, industry, status, and stage.

In terms of syndication strategy, Table 8 shows that in 35.82% of the 455 deals in which SIVCs are involved, funds invest alone. In 47.88% of the deals, SIVCs invest with one or three other investors. Only 9 deals are coinvested by more than one SIVC fund. In the other cases, they invest with other investors that do not necessarily pursue an impact objective.

N. investors per round	**N. rounds**	**%**
1	163	35.82
2	93	20.44
3	65	14.29
4	58	12.75
5	22	4.84
6	19	4.18
7	14	3.08
8	4	0.88
9	7	1.54

10	3	0.66
11	1	0.22
12	2	0.44
13	2	0.44
15	1	0.22
16	1	0.22
Total	*455*	*100*

Table 8 - Co-investments

2.3.3 The economic and financial profile of SIVCs' portfolio companies

In this section, we provide first evidence about the economic and financial status of the companies invested by SIVCs. We focus on the 51 companies for which we were able to collect accounting information relative to the year in which they received the investment, as well as for some years before and some years after the round itself (see Section 3.1 for a detailed description of the sample construction). As previously said, our sample is composed of a maximum of 302 observations relative to 51 companies invested by 22 SIVCs (5.912 years observed on average per company). Table 9 reports the geographical and industrial distribution of this sub-sample of invested firms. Most of the companies is from Europe (64% of the sample). More specifically, 30% of the companies are from UK, while 10% are from France. In terms of industrial distribution, the sample is mainly composed of companies operating in the Financial (25.49%), Professional, Scientific, and Technical activities (15.69%), Information and Communication (15.69%) and Manufacturing (13.73%) sectors.

Company Continent	**Company Country**	**N. companies**	**%**
	Denmark	1	2.00%
	France	5	10.00%
	Finland	1	2.00%
	Germany	3	6.00%
Europe	UK	15	30.00%
	Netherland	1	2.00%
	Norway	3	6.00%
	Poland	1	2.00%
	Sweden	2	4.00%
Rest of the world		18	36.00%
	Total	*50*	*100.00%*

NACE Rev. 2 main section	***N. companies***	***%***
A – Agriculture, forestry and fishing	1	1.96%
B - Mining and quarrying	1	1.96%
C - Manufacturing	7	13.73%
D - Electricity, gas, steam and air conditioning	2	3.92%
E - Water supply; sewerage, waste management	1	1.96%

F - Construction	2	3.92%
G - Wholesale and retail trade	1	1.96%
I - Accommodation and food service activities	1	1.96%
J - Information and communication	8	15.69%
K - Financial and insurance activities	13	25.49%
M - Professional, scientific and technical activities	8	15.69%
N - Administrative and support service	6	11.76%
Total	*51*	100.00%

Table 9 - Geographical and industrial composition of the sample of invested companies.

In Table 10 we provide some descriptive statistics about sample companies at the time of the investment. They are, on average, 11.76 years old (median value 10 years) and this is in line with the observation that the percentage of early-stage companies in the sample is very low (only 19.61% are less than 5 years old at the time of the investment). The difference between mean and median values of the variables Sales and Assets, as shown in Table 10, suggests that these companies present very skewed distributions in terms of size. In what follows, we focus on the median value, that is a more robust and sensible measure, thus better suited to derive a central tendency for skewed distributions. We observe, again, that invested companies are not startups: they show sales around 5 Mln euros and total capital invested of 8.5 Mln euros (1.6 Mln euros in terms of fixed assets) at the time of the investment. A similar reasoning may be applied when considering their leverage: looking at the ratio between financial debt and equity, results indicate a median value of 0.236 at the time of the investment versus a mean value of 0.755. As to their profitability, funded companies show a skewed distribution of profits as well,

with a mean value of 8.8 Mln euros and a negative median value around 46 thousand euros.

Variable	N.Obs.	Mean	Median	St.dev.	Min	Max
Age	50	11.760	10.000	9.997	0.000	63.000
Sales	40	974,465.800	5,064.651	6,010,257.000	0.000	38,000,000
Profit&Losses	42	8,815.954	-46.506	40,815.030	-15,352.760	237,090.500
Total Assets	51	600,246.800	8,516.407	3,310,653.000	50.453	23,600,000
Fixed Assets	44	371,812.900	1,646.830	2,361,587.000	0.000	15,700,000
Financial Debt/Equity	38	0.755	0.236	1.705	-1.643	6.749

Note: Accounting data (Sales, Profit&Losses, Total assets, and Fixed Assets) are in thousand EUR.

Table 10 - Descriptive statistics about invested companies at the time of the investment

We further examine the profitability status of invested companies by disentangling between companies with profit and with losses at the time of the investment to explore, in more details, the investment strategy of SIVCs. At the time of the investment, 21 companies out of 51 (41.18%) show losses, while the remaining 30 companies (58.82%) have profits, as illustrated in the last row of Table 11. This evidence suggests that SIVCs seem to operate according to different investment strategies, without necessarily considering ex-ante profitability as an investment pre-condition.

We posit that a selection of invested companies that is rather irrespective of their profits at the moment of the investment might be associated with the social impact dimension that SIVCs intend to address. Accordingly, we explore the presence of potential differences in the selection of target companies depending on the impact theme declared by SIVCs, as described in Section 3.2. In 54.90% of the

cases, sample companies are invested by SIVCs declaring Energy and Environment as their target impact theme. In the 33.33%, 45.10% and 47.06% of the cases, companies are invested by SIVCs focusing, respectively, on Employment, Finance and Basic Services. Table 11 shows the distribution of firms with profits or losses at the time of the investment, according to the impact theme declared by SIVCs. Results indicate that, when funds aim at targeting the Basic Services and Employment social impact dimensions, they have a higher probability than average to choose companies with losses (54.17% and 47.06% respectively for Basic services and Employment). The opposite is true for SIVCs declaring Energy and Environment and Finance as target investment areas (respectively the 39.29% and 39.13% of investments are in companies with negative profits). Hence, this preliminary evidence supports the view that when SIVCs decide to invest in social impact areas characterized by below-market performances (i.e., Basic Services and Employment), they necessarily must allocate a proportion of their portfolio to investments showing losses.

	Profits/losses of companies at the time of investment		
Social Impact Theme	**Losses**	**Profits**	**Total**
Basic Services	13(54.17%)	11(45.83%)	24 (47.06%)
Employment	8(47.06%)	9(52.94%)	17 (33.33%)
Energy and Environment	11(39.29%)	17(60.71%)	28 (54.90%)
Finance	9(39.13%)	14(60.87%)	23 (45.10%)
Total	**21 (41.18%)**	**30 (58.82%)**	**51 (100%)**

Table 11 - Profits/losses of invested companies at the time of the investment by impact theme

In addition, we consider the growth of invested companies in the years before the entry of the SIVC fund. We estimate the average compounded annual growth rate (CAGR) in the years before the investment. Table 12 reports the CAGR of sales, profits, fixed assets, and total assets of invested companies at the time of the investment. Again, we focus on median values given the skewed distribution of the growth rates, as it clearly appears in Table 12. Results indicate that invested companies show significant growth patterns before the investment date: they show, in the years before the investment, a growth of 38.79% in sales, of 11.39% in profits, of 17.8% in fixed assets and of 40.04% in total assets.

Variable	Median	Mean	St.dev	Min	Max
Sales CAGR	0.388	2.197	6.203	-0.696	32.012
Profit CAGR	0.114	0.351	4.678	-12.388	16.951
Fixed Assets CAGR	0.178	0.901	1.833	-0.401	9.393
Total Assets CAGR	0.400	0.664	0.729	-0.314	2.968

Table 12 - Growth of invested companies at the time of the investment

It is interesting to observe whether growth rates differ between companies with profits or losses at the time of the investment. Descriptive statistics on this issue are illustrated in Table 13. Interestingly, results indicate that companies with losses at the time of the investment have higher growth rates compared to companies with profits, in terms of all the considered dimensions: sales, profits and assets. Overall, this suggests that SIVCs seem not to act as traditional VCs, which cherry pick young ventures with high potential to sustain the consolidation of new entrepreneurial profiles. Instead, they seem to select companies that are already on the market, pursuing two different investment strategies. On the one hand, they may invest in companies with negative results but interesting growth patterns. On the

other hand, they may prefer more established companies with profits supporting an accelerated growth path. The latter approach is coherent with a more "patient" financial approach and potentially linked to the transformation of traditional companies toward more impact-oriented business models.

	Median growth (CAGR) in the years before the investment			
Profits/losses at the time of investment	**Sales**	**Profits**	**Fixed Assets**	**Total Assets**
Losses	0.409	0.158	0.678	0.921
Profits	0.298	0.114	0.135	0.323
Total	0.388	0.114	0.178	0.400

Table 13 - Growth and profits/losses of invested companies at the time of the investment

We expect that some relevant differences may emerge when considering the impact themes declared by SIVCs, as shown in Table 14. When SIVCs target the Basic services and Employment impact themes, they seem to select companies that are heavily investing in technical infrastructures, i.e., showing high growth rates of fixed and total assets. Putting together the results on profit and growth patterns, it appears that the investment strategy for this category of SIVCs aims to sustain companies with low profitability in becoming more capital intensive, thus soliciting investments in technical infrastructures. Hence, in these social impact areas, SIVCs are expected to encourage invested firms engaged in social innovation projects to increase firms' capital intensiveness.

A different picture emerges for SIVCs investing in the Energy and Environment social impact theme: in this case, funded companies are already endowed with technological and fixed capital stock and the entry of a SIVC fund is less connected with the introduction of investment patterns in new technology. In case of funds

targeting Finance as an impact theme, we interpret our evidence in the light of the microfinance domain: invested companies are not growing in terms of fixed assets but they show an increasing trend in current asset activities (such as account receivables).

	Median growth (CAGR) in the years before the investment			
Social Impact Theme	**Sales**	**Profits**	**Fixed Assets**	**Total assets**
Basic Services	0.406	0.572	0.677	0.887
Employment	0.409	0.396	0.458	0.737
Energy and Environment	0.319	0.065	0.137	0.202
Finance	0.449	0.216	0.458	0.720
Total	0.388	0.114	0.178	0.400

Table 14 - Invested company's growth (CAGR) after the investment by SIVCs.

We finally provide some evidence about the impact of SIVCs on investee companies. Out of 51, a total of 41 companies (80.39%) are still active, while the remaining 10 are dissolved. As to the growth of invested companies after the entry of a SIVC fund, Figure 3 reports the trend of sales and fixed assets over time (i.e., scaled values considering the variable fixed to a value of 100 in the year of the investment).

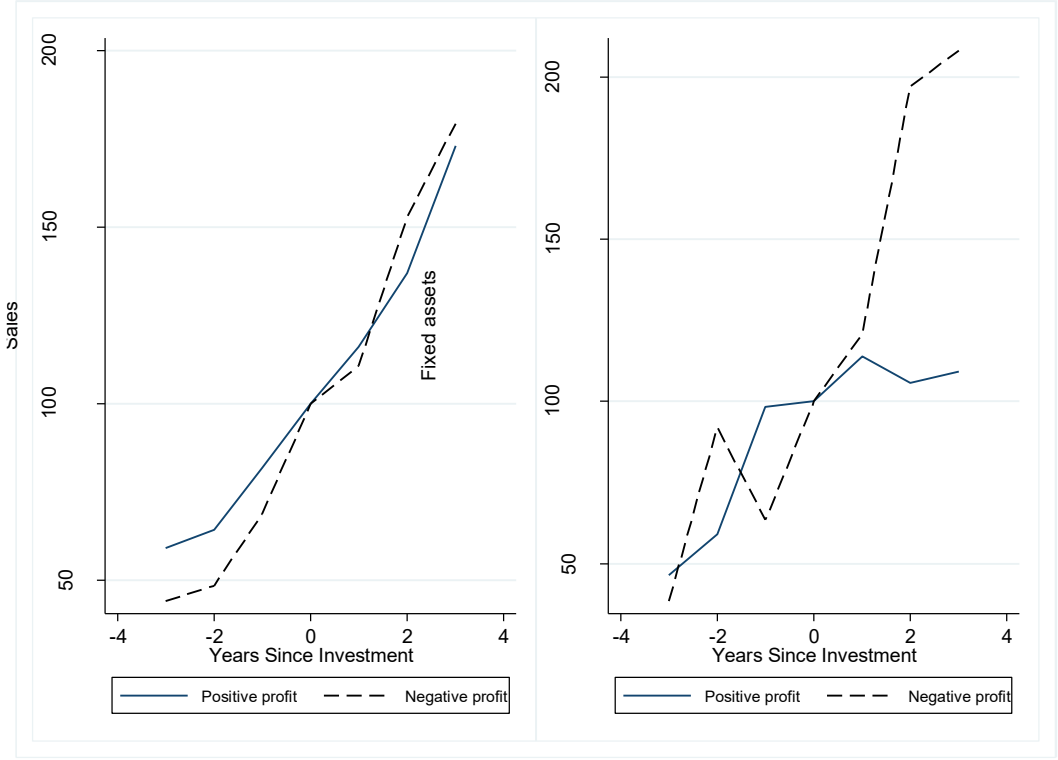


Figure 3 - Trend in sales and fixed assets of invested companies around the investment year

Figures indicate that SIVCs seem to have a positive impact on invested companies in terms of both sales and investments in fixed assets. According to the numbers shown in Table 15, in the years following the investment by a SIVC fund, the average CAGR of sales and fixed assets is, respectively, 44.90% and 14.82%. Again, significant differences emerge between companies with losses or profits at the time of the investment: companies showing losses at the time of investment grow more in sales: on average, their growth is 63.03% in the years following the investment versus 18.94% for those with profits. Similarly, we observe a CAGR of fixed assets equal to 50.45% for companies with losses, while the same value is equal to 13.47% for firms with profits at the time of the investment.

This result is in line with the observation that SIVCs likely endorse different investment strategies: on the one hand, they seem to invest in companies with a poor profitability to sustain their investment growth (we verified that this happens

especially for Basic Services and Employment social impact themes). On the other hand, especially when the prevalent impact theme is Energy and Environment or Finance, SIVCs invest in companies with profits, whose growth patterns, in terms of investment in fixed assets, is less pivotal in their corporate strategy. In any case, the impact of SIVCs seems to be positive in boosting both sales and fixed assets over time. It is interesting to observe that invested companies already show growing patterns before the investment and SIVC financing seems to amplify this growth in terms of both sales and fixed assets.

Profits/losses at the time of investment	Median Sales CAGR	Median Sales CAGR
Losses	0.630	0.504
Profits	0.189	0.135
Total	0.449	0.148

Table 15 - Invested company's growth (CAGR) after the investment by SIVCs.

2.4 Econometric analysis

In addition to the abovementioned descriptive statistics, we further explore the characteristics associated to the performance of SIVCs, through an explorative multivariate analysis on the 48 companies for which we collected accounting data.

In particular, we estimate a series of regression models where the dependent variables are proxies of growth, in order to provide preliminary evidence about the impact of SIVCs on the performance of invested companies. More in details, we consider two dependent variables: the amount, in logarithms, of total assets and the amount, in logarithms, of total sales.

We estimate a series of augmented Gibrat law panel-data models (Evans 1987) derived from the model specification used by Croce, Martì, and Reverte (2019).

This model is standard in the industrial organization literature on company growth (Sutton 1997) and allows us to test whether the growth rates of SIVC-backed companies increase after the investment. According to this growth model, our control variables include the logarithm of the dependent variable in the previous year and age in logarithm. Country, year and industry fixed effects are also included.

The impact of SIVCs is estimated, first, in Model I, by introducing a dummy stepit taking value 1 from the year of the SIVC investment onwards. It represents an averaged effect of SIVCs over time. Secondly, in Model II, in order to explore whether there is a time effect in the impact of SIVCs, we disentangle the impact over time by introducing two dummy variables indicating the short and the long-term effects of the SIVC investment. The first dummy, shortit is a dummy variable taking value 1 from the year of the investment until 2 years after the receipt of capital by a SIVC (e.g., from year 0 to 2). The second dummy, longit is a dummy variable taking value 1 starting from the third year after the receipt of capital from a SIVC (e.g., from year 3 onwards). Finally, in Model III, we estimate the impact of SIVCs as a shock effect by including only a dummy shockit taking value 1 only in the year of the receipt of the SIVC investment (e.g., in year 0).

Using OLS and fixed effects to estimate Gibrat law models may result in biased estimates of the parameters (Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998). Moreover, these methods either do not (in the case of OLS) or only partially (in the case of fixed effects) control for unobserved heterogeneity. We address these problems by using random effects (RE) and the system generalized method of moments (GMM-SYS) approach (Blundell and Bond 1998). Specifically, we implement the GMM-SYS estimation procedure with moment conditions for endogenous variables (i.e., lagged size and SIVC related variables). We also include the finite sample correction for the two-step covariance matrix developed by Windmeijer (2005). Age, year, industry, and country dummies

are used as external instrument. The GMM methodology on panel data allows us to estimate the effects of SIVCs on the growth of invested companies.

Results of Model I, Model II and Model III are reported in Table 16, Table 17 and Table 18, respectively. In particular, the first two columns of each Table refer to the model in which total assets is used as dependent variable, while in the last two columns, we report estimates about sales. For each dependent variable, the first column reports RE estimates, while the second column refers to GMM estimates.

	Total Assets		**Sales**	
	RE	GMM	RE	GMM
lag size	0.8060***	0.9116	0.7265***	-1.1834
	(0.051)	(0.905)	(0.067)	(0.880)
step	0.2978**	1.8499*	0.2933	-15.111
	(0.143)	(1.011)	(0.246)	(0.955)
Log Age	-0.0717	-2.3442	-0.0778	22.0977
	(0.143)	(2.791)	(0.275)	(14.708)
Const	1.9683***		2.5627***	
	(0.489)		(0.728)	
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N. obs	191	191	147	147
N companies	48	48	36	36

Table 16 - Impact of SIVCs: estimates of Model I

	Total Assets		Sales	
	RE	GMM	RE	GMM
lag size	0.7922***	1.1779	0.7362***	0.2284
	(0.052)	(0.801)	(0.065)	(0.388)
short effect	0.2887**	1.2435*	0.3188	0.9959
	(0.144)	(0.709)	(0.238)	(0.618)
long effect	0.0873	1.6848*	1.0265***	1.8082**
	(0.214)	(0.948)	(0.342)	(0.802)
Log Age	-0.0102	-8.6935	-0.1764	4.2728
	(0.150)	(8.063)	(0.268)	(5.105)
Const	2.0734***		2.2037***	
	(0.501)		(0.715)	
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N. obs	191	191	147	147
N companies	48	48	36	36

Table 17 - Impact of SIVCs: estimates of Model II

	Total Assets		Sales	
	RE	GMM	RE	GMM
lag size	0.8252***	0.8320	0.7347***	-0.6615
	(0.051)	(1.626)	(0.067)	(0.501)
shock	0.2624**	1.9512*	-0.0035	2.6780
	(0.128)	(1.094)	(0.219)	(2.034)
Log Age	-0.0270	-2.2314	-0.0758	12.6328
	(0.140)	(3.419)	(0.277)	(7.981)
Const	1.9973***		2.8619***	
	(0.482)		(0.692)	
Country dummies	Yes	Yes	Yes	Yes
Industry dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
N. obs	191	191	147	147
N companies	48	48	36	36

Table 18 - Impact of SIVCs: estimates of Model III

Looking at the estimates in Table 16, our results indicate a positive and significant impact of SIVC investments on the size of the invested companies in terms of total assets. In fact, both RE and GMM estimates suggest that receiving SIVC funding determines an increase of total assets in the years following the receipt of capital. This result does not hold when we look at sales, this suggesting that, while the receipt of capital induces companies to invest money in assets, this

is not associated to an improved route to market in terms of facilitating an increase in sales.

When we disentangle between short- and long-term effects, as reported in Table 17, our analysis produces more interesting insights: the effect of SIVCs on assets is concentrated in the first years after the receipt of capital. This is in not surprising, as, being cash part of the tangible assets, the resulting effect of the invested capital is a growth of total assets in the balance sheet. Conversely, this attitude does not continue in the following years as the long-term effect of SIVCs is not significant in the long run.

Looking at sales, estimates in Table 17 suggest that, even though the average effect of SIVCs after the investments is not significant, there is a positive and significant effect of SIVCs in the long run, this meaning that invested companies are able to grow, in terms of sales, after the entry of SIVC investors, but this requires time.

These different types of effects are confirmed when we look at estimates in Table 18, in which the impact of SIVCs is modelled as a shock. Estimates confirm a positive and significant shock effect on total assets and a not significant effect on sales involved by the entry of SIVCs in the equity capital of the invested companies.

2.5 Conclusions

SIVC financing represents a novel and important opportunity for entrepreneurs to raise capital for their social entrepreneurial ventures. Despite the recent turmoil in the global financial markets, SI finance seems to face a positive momentum. Given its recent nature, the phenomenon has been largely understudied and this is, to our knowledge, one of the first works offering exploratory insights into this domain.

In this study, we have mapped the SIVC landscape and assessed the impact of these investments on social enterprises. We have described how these newly born VC funds operate in terms of their investment dynamics, tapping into specific attributes peculiar to the social investment panorama, such as the different kind of societal impact that funds strive to achieve. We have presented first evidence about the economic and financial status of the companies invested by SIVCs. Additionally, running multiple regression models, we have assessed the impact that SIVCs have generated on invested firms. Results indicate that SIVCs seem not to act as traditional VCs, which are oriented toward the selection of high growth young ventures. Instead, data reveal that they invest in companies that are on the market since long time and that show nontrivial annual growth rates of sales, profits, fixed assets and total assets in the years before the investment. We observe that SIVCs are likely to pursue two different investment strategies. On the one hand, they select companies with negative profitability results but interesting growth patterns. This happens especially when funds indicate Basic Services and Employment as the impact themes they intend to address: they target companies that are heavily investing in technical infrastructures to sustain their capital intensiveness efforts. On the other hand, SIVCs do not disregard more established companies with profits but a reduced prospective of growth at the time of the investment.

While we do not observe significant improvements in the sales figures in econometric analyses, all the models show that total assets have been positively affected by the new equity raised. However, when we disentangle between short- and long-term effects, our analysis reveals that the effect of SIVCs on total assets is concentrated in the first years after the receipt of capital, while it disappears in the following years. A positive and significant effect of SIVCs on sales is instead found in the long run.

While the picture is intriguing, it represents just a first foray into the state of the art and the trajectories affecting the development and implications of SIVC

financing. Even if SIVC still makes up a small proportion of VC financing, we believe that our explorative analysis offers new insights that should be of interest to entrepreneurial finance and business scholars. As the phenomenon grows in size and the field moves from its infancy to a certain level of development, interesting avenues for future research may be opened up. The understanding of the processes and dynamics affecting the evolution of the SI ecosystem and the role played by SIVCs, as well as the degree of interaction with the other stakeholders, needs to be further elaborated. How does the level of engagement of SIVCs with other players in the SI landscape (e.g., SI business angels, philanthropic investors, ...) influence the selection, evaluation and negotiation of the deals? Are these relationships characterized by complementarity or substitutability and is this affecting their decision-making process? Understanding to what extent the positioning of SIVCs in the SI ecosystem and their interactions with other players in the field affects their investment strategy is clearly left for future studies.

Alternatively, future research might examine the complex interplay between the financial and the SI logics in the investment strategies of SIVCs. What are the factors driving the prevailing dominance of one logic over the other? How do internal and external social and economic changes affect the configuration of SIVCs' investment logics and business models? What are the consequences on investees' performance and mission in case of SIVCs' style drifts (ex. social logic suppressed by the dominance of the financial logic)? The adoption and integration of different theoretical paradigms and perspectives to explain these issues is a ripe area for further exploration.

A final dimension of investigation that is rich in potential for future research concerns syndication patterns. How often do SIVCs syndicate? Which synergies may arise between SIVCs and traditional VC investors? What are the characteristics of VC funds they co-invest with (e.g., in terms of experience, investment strategy, stage focus)? All these areas of inquiry still remain to be investigated.

As always, our work is not exempt from limitations that can, however, stimulate further research in the field. First, we derived our data on SIVCs and their invested ventures from privately managed databases, which are limited in the richness of the information they provide. Available data does not allow, for example, to account for a deeper analysis of the heterogeneity of SIVCs in terms of their reputation, stated objectives, value added provided to portfolio companies. This opens up the possibility to build up richer data sources by adding more in-depth and qualitative information on their characteristics and the way they operate. Second, an assessment of the impact SIVCs exert on investee ventures might be performed, by enlarging the number of invested companies for which accounting data are available and considering appropriate control groups of both ventures backed by non-SIVCs and non-invested ventures. The numbers of the sample considered in our analysis does not allow us, at the moment, to pursue this research direction. Third, future research may explore, for example, whether the effects of SIVC investing on the companies invested may change considering different stages of development of the SIVC industry or different economic cycles.

Our findings have implications for policy. Policy makers are today well aware that the flow of funds into SI ventures needs to grow in the future to tackle pressing social needs (Davies, Haugh and Chambers 2019; Royal Society 2012; WBCSD 2013). In order to stimulate SIVC financing, the basic investment infrastructure needs to be developed further, in order to ensure acceptable returns for SIVCs. The lack of standardized and universally recognized metrics to measure the social return of an investment is an obstacle to the growth of SI investments, because it makes the process of benchmarking social returns difficult and hence limits the evaluation of the extent of the impact generated. Given the potential for expansion of the SIVC market, government intervention is desired to provide an appropriate regulatory framework to sustain risk capital in this financial domain. For example, a legislation to unleash conservative legal and policy requirements for SIVC funds is fundamental to create a SIVC market. Policy makers should also be mobilized to

incentivize the development of standardized and transparent industry-wide measures.

Our work also suggests implications for both entrepreneurs seeking SIVC funding and for SIVCs. From the perspective of the recipients of SIVC finance, we have shown that the economic benefits of being backed by a SIVC are significant, in terms of stimulus to their growth. However, in order to gain the most of advantage from the relationship with a SIVC, SI entrepreneurs should have a deeper and better understanding of this new type of VC, which is looking beyond the 'quick-win investment format" (Bocken 2015). Entrepreneurs should carefully consider how to develop their entrepreneurial ideas to properly target SIVCs. This might imply a reconsideration of their hybrid nature, which is reflected in the co-existence in their mission of the twofold aim of addressing social needs and growing their business. In other words, SI ventures should better balance the achievement of social impact with their commercial development if they want to be attractive for SIVCs.

An exploratory scenario of SIVC financing patterns is useful for VC investors too. VC investors need to deepen their understanding of how the market is evolving, in order to design and implement new investment structures and assessment metrics compatible with social impact constructs. One of the key constraints that today still limits VC investors' decisions to invest in SI ventures is linked to the shortage of "investment ready" deals, namely high-quality investment opportunities showing some track record (Oleksiak, Nicholls, and Emerson 2015; Saltuk et al. 2014). It is clear that SIVCs will likely not invest in those ventures where they cannot predict a clear financial return. In this arena, application of conventional portfolio tools used by traditional VCs to evaluate the risk and return spectrum of an investment opportunity should be revised and adapted to jointly evaluate financial and social returns. This framework should include other paradigms, such as the social risk (Brandstetter and Lehner 2015), which are not aligned with the dictates of the

traditional VC industry, to be able to fully assess the risks associated with the generation of impact. As our analysis reveals, SIVCs have a positive impact on both the investee's total assets (in the short term) and sales revenues (in the long term). As soon as an increasing number of SIVCs is able to generate positive returns (to the investees in terms of economic impact and to their limited partners in terms of market-rate returns), the market is predicted to expand, with the attraction of new funds and the entry of new traditional VC players. We are confident that the insights presented in the work represent an important starting point to understand the whole SI investment phenomenon.

Chapter 3

Looking at the future of blockchain technology from different perspectives

Note: this chapter includes material as published in the article: "Levis, D., Fontana, F., & Ughetto, E. (2021). A look into the future of blockchain technology. Plos one, 16(11), e0258995."

3.1 Introduction

Over the last few years, the hype and interest around blockchain technology have consistently increased. VCs from all over the world have started betting on blockchain-enabled applications, pouring more than $30 billions of investments in blockchain start-ups in 2021 alone[7]. Practitioners from many industries and sectors have joined an open, yet mainly unstructured, discussion on the potential disruptive capabilities of this newly born technology (Bender et al. 2019; Carson et al. 2018; Crosby et al. 2016). In this chapter, we use the findings obtained using a well-known forecasting methodology to understand the feeling and consensus about the future potential of such a new technology from an heterogeneous pool of experts, and then drive conclusions comparing them to the investment choices of venture capitalists. Are VCs betting on the next internet or are we witnessing the growth of a technological and financial bubble?

[7] ETF Database, 2022

In principle, the size of the phenomenon could be huge, with latest estimates predicting blockchain to store, by 2025, the 10 per cent of the world's GDP (about $88tn in 2019) (Zalan T. 2018). However, the complexity of the technology itself and the difficulties in assessing its impact across the different application fields have prevented the social, industrial, and scientific communities to agree upon a shared vision of future blockchain-based scenarios. Very fundamental questions are still to be answered. Which blockchain-enabled applications will see the light in the next few years? Which industrial sectors will be mainly affected? How will companies react to potential industry-disruptors? How will the current societal paradigm shift? Which role will policy makers play in enhancing this new paradigm?

All these unsolved interrogatives, coupled with the increasing attention that blockchain-based start-ups are receiving from venture capitalists spur the underlying question that motivates this chapter. Are VCs investing in a promising and impactful technology? Or, looking at the same question from a more financial perspective, are VCs efficiently allocate capital to start-ups with the potential to radically change (for the better) our society?

Despite the great and undoubted innovation linked to this technology, uncertainties and speculation on the potential scenarios still animate the industrial and scientific dialogue (Islam et al. 2021). It is not yet clear which applications will see the light, and, eventually, what effects these changes will have at a societal level.

In this chapter, we start from the findings obtained using a Delphi approach that investigate whether and to what extent blockchain-based applications will affect firms' organizations, innovations, and strategies by 2030, and, consequently, which societal areas will be mainly affected. With this methodology, we reached experts' consensus to gain new insights and assess the likelihood about the future of the technology. This is a relevant issue, as blockchain technology applications

cover a wide spectrum of areas. Blockchain can be applied vertically within an industry (e.g., disrupting its supply chain) or horizontally across different industries or within single companies (e.g., modifying the internal structures and the modus operandi of the different company functions). Given the number of potential applications and the complexity of the technology, stakeholders are polarized into opposite categories: the true believers, who bet the technology to enable a disruptive paradigm' shift soon, and the doubters, who are convinced that the technology has still to mature to have a real impact on society, if ever it will have one.

The findings are then compared to investment trends in blockchain start-ups from venture capitalists, to assess whether experts and investment professionals agree upon the scenarios that will likely happen in the future, and thus, the technologies that will enable those scenarios. The aim is to understand if venture capitalists, who are pouring billions into blockchain-based start-ups, are believing in the same scenarios that experts foresee to be the most likely to happen.

The literature on blockchain is also widely fragmented. Different works have investigated possible blockchain applications within specific domains, such as finance (Bunchak et al. 2018; Cai CW. 2008; Cocco et al. 2017), logistics (Dujak et al. 2019), healthcare (Angraal et al. 2017; Kuo et al. 2017) and education (Chen et al. 2018). However, a holistic approach on possible blockchain-enabled future scenarios is still missing. To our knowledge, the only contribution in this direction is the one by White (White GR. 2017), who explores blockchain as a source of disruptive innovation exclusively with regard to the business field. We depart from his work to adopt a much wider perspective in this study. In fact, our aim is to obtain a deep understanding on how the adoption of this technology in Europe will lead to changes over multiple dimensions, ranging from business to culture and society, policy and regulation, economy and technology. Thus, our research aims at exploring if a convergence between the two divergent perspectives on blockchain

can be found, bringing together experts currently working on blockchain projects to explore the possible changes that the technology will bring to the society by 2030.

This chapter aims at contributing to different literatures. Firstly, it is contributing to the raising blockchain literature by offering a holistic view on possible blockchain-enabled future scenarios in Europe, and by investigating which of the proposed scenarios is more likely to occur. Secondly, it contributes to the venture capital literature as well, by comparing VC investments in blockchain (from publicly available sources) to the scenarios that experts believe are most likely to occur by 2030.

As widely agreed by the academic literature, technological developments dictate the speed and pace at which societies change (Jian et al. 2017). Under this assumption, technological forecasting appears to be a method of fundamental importance to understand "ex-ante" the potential development of technological changes, and their impact on different societal aspects (Firat et al. 2008). Foreseeing future technological trends could help society in understanding possible future scenarios, thus contributing to a better knowledge of the new paradigms our society is heading towards. The chapter is structured as follows. Section 3.2 provides an overview on the main research streams upon which this work is based. Section 3.3 presents the methodology. Results are described in Section 3.4 and Section 3.5 concludes this chapter.

3.2 Background literature

3.2.1 The Blockchain Technology

As defined by Crosby et al. (2016) a blockchain can be conceptualized as a shared and decentralized ledger of transactions. This chain grows as new blocks (i.e. read transactions or digital events) are appended to it continuously (Pilkington et al. 2016; Zheng et al. 2018). Each transaction in the ledger must be confirmed by most of the participants in the system (Crosby et al. 2016, Narayanan et al. 2016;

Nofer et al. 2017; Swanson T. 2015; Treleaven et al. 2017). This means for the community to verify the truthfulness of the new piece of information and to keep the blockchain copies synchronized between all the nodes (i.e., between all the participants to the network) in such a way that everybody agrees which is the chain of blocks to follow (Nofer et al. 2017). Once the users verify the transaction with a process called mining, a new block is added to the chain. Usually, the miner (i.e., the user participating to the verification process) receives a reward under the form of virtual coins, called cryptocurrencies. Examples of cryptocurrencies are Bitcoins, Ether, Stellar Lumens and many others. Virtual coins can then be used on the blockchain platform to transfer value between users (Zheng et al. 2018; Narayanan et al. 2016; Nofer et al. 2017).

Thanks to a combination of mathematics and cryptography, the transactions between users (i.e., exchange of data and value), once verified by the network and added to the chain, are "almost" unmodifiable and can be considered true with a reasonable level of confidence (Zheng et al. 2018; Nofer et al. 2017, Yaga et al. 2019). These attributes of the technology make it extremely efficient in transferring value between users, solving the problem of trust and thus potentially eliminating the need of a central authority (e.g., a bank) that authorizes and certifies the transactions (Cai CW. 2008; Guo et al. 2016; Anagnostopoulos I. 2018).

The technology can be easily applied to form legally binding agreements among individuals. The digitalized asset, which is the underlying asset of the contract, is called token. A token can be a digitalized share of a company, as well as a real estate property or a car. Through the setting of smart contracts (i.e., digitalized contracts between two parties), the blockchain technology allows users to freely trade digital tokens, and consequently to trade their underling physical assets without the need of a central authority to certify the transaction (OECD, 2020).

3.2.2 Blockchain Technology Applications

The academic literature has investigated a wide range of possible blockchain applications within specific domains, such as finance (Bunchak et al. 2018; Cai CW. 2008; Cocco et al. 2017), logistics (Dujak et al. 2019), healthcare (Angraal et al. 2017; Kuo et al. 2017) and education (Chen et al. 2018).

As mentioned, one of the undoubted advantages of the blockchain technology is the possibility to overcome the problem of trust while transferring value (Kuperberg M. 2019). Not surprisingly, the technology seems to find more applications in markets where intermediation is currently high, like the financial sector, and the FinTech sector, that has recently experienced a consistent make-over thanks to the diffusion of digital technologies (Cai CW. 2008; Arner et al. 2015; Haddad et al. 2019). The implementation of the blockchain technology in the financial markets could provide investors and entrepreneurs with new tools to successfully exchange value and capitals without relying on central authorities, ideally solving the problem of trust. This is among the reasons why many observers believe that the blockchain would become a potential mainstream financial technology in the future (Jagtiani et al. 2020). Blockchain represents an innovation able to completely remodel our current financial system, breaking the old paradigm requiring trusted centralized parties (Bunchak et al. 2018; Cai CW. 2108; Cocco et al. 2017). With new blockchain-based automated forms of peer-to-peer lending, individuals having limited or no access to formal financial services could gain access to basic financial services previously reserved to individuals with certified financial records (Larios-Hernández GJ. 2017). Indeed, blockchain technology can provide value across multiple dimensions, by decreasing information asymmetries and reducing related transactional costs (Block et al. 2018). Initial coin offerings (ICOs) represent one of the most successful blockchain-based applications for financing which has been currently developed. Virtual currencies like Bitcoins can disruptively change the way in which players active in the business of financing

new ventures operate (Cai CW. 2008; Block et al. 2018; Huang et al. 2020; Kher et al. 2021; Masiak et al. 2020). Through an ICO, a company in need of new capital offers digital stocks (named token) to the public. These digital tokens will then be used by investors to pay the future products developed by the financed company (Block et al. 2018; Block et al. 2020; Catalini et al. 2018). ICOs represents a disruptive tool: entrepreneurs can now finance their ventures without intermediaries and consequently lower the cost of the capital raised (Huang et al. 2020; Adhami et al. 2018). However, some threats coming from the technology adoption can also be identified, as blockchain can also lead to higher risks related to the lower level of control intrinsically connected to the technology, especially in the case of asymmetric information between the parties involved.

Disintermediation plays a key role in the healthcare sector as well, where blockchain has recently found numerous applications. Indeed, many players currently need to exchange a huge amount of information to effectively manage the whole sector: from hospitals, to physicians, to patients. The ability to trustfully exchange data and information becomes of undoubted value in this context (Angraal et al. 2017; Kuo et al. 2017). It should not be difficult to envision blockchain applications in other fields as well. In every sector in which information, value, or goods are supposed to flow between parties, blockchain can enable a trustful connection between the players, with the need of a central body entrusting the transaction. Within supply chain, it can increase security and traceability of goods (Dujak et al. 2019, Francisco et al. 2018). Within education, it can help in certifying students' acquired skills, reducing, for example, degree fraud (Chen et al. 2018). To conclude, a recent work from Lumineau et al. (Lumineau et al. 2021) highlights possible implications of the technology in the way collaborations are ruled and executed, shading light on new organizational paradigms. Indeed, the authors show how the intrinsically diverse nature of the technology could strongly affect organizational outcomes, heavily influencing and

modifying (possibly improving) the way in which different entities cooperate and collaborate.

3.2.3 VC investments in blockchain

The academic literature on venture capital investments in blockchain-based start-ups is very limited. Aside from the literature focusing on Initial Coin Offerings (ICOs) as a substitute for venture capital financing (Akbarpour, 2019; Lin et al., 2019; Tapscott et al., 2017 and others) few works have dealt with specific VC investment trends in blockchain-based start-ups. Among them, the research carried out by Friedlmaier et al. (2018) is of particular interest for the purpose of this chapter. By using a novel dataset including global blockchain start-ups (1,140 companies) and the relative VC investments ($1,5 billions), they provide the first structured overview of blockchain start-ups and venture capital investments in this sector. Interestingly, they were able to investigate geographical, industry, and financial aspects. To the end of merging the considerations coming from industry experts to the financial operations performed by investment professionals, it is interesting to look at the distribution of VC investments in blockchain start-ups over different industries and product/service offering. As reported in Friedlmaier et al. (2018), few industries/sectors gather most venture capital investments in blockchain start-ups. Finance & Insurance, and Information & Communication ventures represent the 80% of the VC-backed companies in terms of frequency and sum up to more than 95% of the deployed capital. Geographically, two clusters seem to be emerging by the analyzed sample: USA and Europe account for almost 80% of the total number of companies in the dataset.

Aside from the yet scarce academic literature on the topic, it is interesting to explore the growing body of practitioner-based reports which give useful insights on the topic. Interestingly, dedicated blockchain venture capital funds have been reported to overperform (in terms of internal rate of return) their more generalist

peers in the seven years ranging from 2014 to 2021[8], although invested volumes remain a relatively small fraction of the whole VC market. This consideration suggests that such investments, and consequently the relative start-ups, tend to rapidly gain value, even faster than other more traditional venture backed sectors. To the end of this study, this reflection points in the direction of good selection capabilities of VCs, that seems to be investing in high-value, fast growing companies. However, in contextualizing this observation, it must be noted that the crypto market (that heavily correlates with the performance of blockchain dedicated VC firms) has witnessed an incredible bull run over the last few years, but also a sharp decline in 2022. Any comparison on the performance of the funds, should look at more longer horizons to be somehow informative and robust. Coherently with the findings from Friedlmaier et al. (2018), four out of the five blockchain start-ups that received the greatest amount of funding in 2020 operate in the financial technology industry, confirming the belief from VCs that blockchain is going to heavily disrupt such industry[9], at least in a first place.

This brief literature review gives a hint on the sectors that VCs believe will be the ones more affected by the adoption of the blockchain technology. By comparing these and other findings with the results obtained through the Delphi forecasting technique, we will be driving further considerations on the consensus between investment professional and industry experts on which future scenarios are more likely to occur by 2030.

3.3 Methodology

As previously mentioned, the scope of this chapter is to compare the beliefs of investment professionals and industry experts on which blockchain-enabled

[8] Cointelegraph Consulting Venture Capital Report, 2021
[9] Cointelegraph Consulting Venture Capital Report, 2021

scenarios are most likely to occur by 2030 in Europe. To this end, two approaches have been used: from one side, using the Delphi forecasting techniques it has been possible to gather and analyze consensus among key opinion leaders. From the other side, analyzing the available literature (although limited) and investment trends it has been possible to understand which sectors have been more heavily invested by VCs. Comparing these findings offer an interesting and novel picture on the level of agreement between industry experts and venture capitalists on the shape of a blockchain-enabled future.

3.3.1 Delphi Forecasting Technique

The Delphi method is a forecasting technique used to investigate possible technology-enabled paradigm shifts. It is one of the many forecasting techniques that have been developed and used in the past decades and it is based on a very structured and peculiar process. Many academic works have adopted this methodology (although in various shapes) since its development (Jian et al. 2017; Chou C. 2002; Donohoe et al. 2012; Gordon TJ. 2009; Gordon et al. 2006; Kameoka et al. 2004; Markmann et al. 2013). As the core of the Delphi approach, experts are iteratively required to evaluate projections (representations of possible futures) and assess their societal impact and the likelihood that they will occur within a specific time horizon.

While most forecasting methods does not account for the technological implications on the social, economic, and political contexts, the Delphi technique allows for consideration of changes in contexts which are interconnected (Porter et al. 2011). Although many different variants of the Delphi methodology have been developed, this research builds on top of the findings obtained from the four-steps Delphi procedure suggested by Heiko and Darkow (Heiko et al. 2010). Although going into the details of the procedure is outside the scope of this research, it is useful to understand how the forecasting technique works to appreciate the level of depth of the scenarios that are deemed to be more probable to occur. The approach

is structured as follow: firstly, several different projections (i.e., representation of possible futures) are built. Then, a panel of industry experts is selected. The selected key opinion leaders are required to assess both the likelihood and impact of all the different scenarios through an iterative procedure in which divergent projections (i.e., representation of a possible futures on which experts do not reach consensus) are evaluated over two rounds of assessment. Eventually, data are analyzed, and projections are grouped into scenarios which are most likely to occur according to the selected panel of experts.

By interviewing experts, attending conferences, and performing desk research, 20 projections have been developed dealing with different societal aspects. Projections have been formulated describing the impact of blockchain on socio cultural, policy and regulation, economic, technological, and business aspects. The projections have been designed to describe in a concise and clear way what could be the implication of the adoption of the technology on the specific area and consequently allow experts to assess their likelihood and overall impact. Notably, many of the projections formulated deal with financial aspects, highlighting the intrinsic potential of the technology to impact the way in which value is managed and transferred. The projections span from assessing the impact on education and knowledge, to cryptocurrency adoption, access to loan, and many other aspects that could be heavily disrupted by 2030.

After having formulated the projections, a panel of 35 knowledgeable experts has been selected to assess the likelihood and impact of the designed projections. The experts, coming from a variety of heterogeneous fields (i.e., academia, consulting, law, business development, …) and with different level of seniority in the industry (with 60% of the sample having at least 3 years of related working experience) have been asked to take part to two rounds of surveys (delivered through internet). Each participant to the process has been provided with the

accurate description of each one of the projections and has been asked to assess, using a five-point Likert scale (Allen et al. 2007) the likelihood and impact of the projections. The probabilities corresponding to the five-point Likert scale have been: 0%, 25%, 50%, 75% and 100%. The advantage of using a quantitative measurement (i.e., a five-point Likert scale) has been to be able to perform quantitative analysis on the results of the survey. The experts were also given the opportunity to give qualitative feedbacks on the projections, that has been extremely useful to build the final scenarios and to compare the results of the Delphi with the investment behaviors of venture capitalists. Using standard statistical tools (such as central tendency measures) it was possible to assess which projections reached experts' consensus on being the most likely to occur (and linking them their relative perceived impact). Projections that did not reached consensus (meaning that a high variability in assigned probabilities was measured) were administered to experts in a second round, to re-assess both their likelihood and impact.

3.4 Results

3.3.1 Interpretation of Delphi projections

Firstly, it is interesting to analyze which projections, out of the initial 20, reached a significant consensus and were given a high probability of occurrence by the experts. We can summarize the findings in this domain around three major axes: efficiency, security, and innovation.

By 2030, it will be easier, faster, and leaner to exchange value and data among users, institutions, and countries. Efficiency will boost and uncover innovation potential within companies and societies if these latter will be able to exploit such a new opportunity. Policies will be a necessary pre-requisite for companies to be able to build a competitive edge globally. From this perspective, the capability of central governments to spur innovation with lean and flexible regulations will be a key driver in explaining the ex-post productivity differential among companies

belonging to different countries. From the interview with an investment banker part of the BPCE French group (one of the largest banks in France), it emerged how efficiency is often hampered by the lack of an equally efficient regulation. To provide the reader with an interesting example, in 2018, Natixis, the international corporate and investment banking, asset management, insurance and financial services arm of BPCE, entered the Marco Polo consortium, an initiative born to provide a newly conceived trade and supply chain finance platform, leveraging Application Programming Interfaces (APIs) and blockchain technology. Many other leading banks joined the consortium as well. However, as highlighted by the investment banker, the main limiting factor of the consortium, strongly hampering its efficiency and ability to provide a competitive edge, was the "old-style" bureaucracy linked to it. Although transactions were in principle to be executed smoothly, a bulk of legal paperwork was required to approve them formally. In this case, it appears evident that technology often runs faster than policy, consistently lowering its potential. Interestingly, this view is also shared by regulatory bodies. An experienced lawyer and notary, also member of a panel of experts elected by the Italian government to define the national strategy on blockchain, highlighted that, sometimes, regulators working on blockchain-related policies are trying to adapt existing regulations to the new paradigm. Due to the intrinsically different nature of the technology, this could represent a wrong approach. At the same time, building a new set of policies from scratches could represent a challenging task. From this perspective policy and technology should come hand in hand to synergically boost productivity. The three projections reached consensus after the two rounds and were assigned a high probability of occurrence. Overall, it is evident that regulatory aspects linked to the adoption of this new technology shall not be underestimated.

As previously mentioned, security, and specifically cybersecurity, is another dimension around which blockchain could bring consistent advantages. This is not

surprising as the whole technology focuses on reducing, by design, the problem of trust. Being blockchains almost impossible to be hacked, they provide an incredibly valuable tool to ensure data protection and security against cybersecurity attacks. Many of the experts which have bene interviewed, were particularly interested in this specific aspect, as cybersecurity concerns following the digitization of many businesses represent a key priority in the agenda of decision makers. From this perspective, and given the increasing costs that companies are facing due to cybersecurity attacks, blockchain could represent an advantage from two different perspectives: from one side to protect companies' digital assets, and from the other side to drastically reduce costs related to attacks. Given the centrality of data in today's businesses, serious attacks and loss of data could represent a serious threat to business long-term sustainability.

The third relevant aspect on which blockchain will have a strong impact is, not surprisingly, innovation. Although regulation could represent a non-negligible limiting factor, experts foresee many sectors to be impacted by the technology adoption. For example, the financial sector could be heavily affected by this new paradigm. Particularly, companies' capital structures and their strategic interlink with business models will drive a differential competitive power. Most likely, enterprises will have to rethink their business models to account for the possibility to digitize/tokenize their assets. The capability in flexibly adapting their service offerings to the new opportunity and the ability to raise, and re-invest, new capitals will shape the global competition landscape across different industrial sectors and geographies. From one side, blockchain will enable new strategic decisions, from the other side, it will be of fundamental importance to build technological capabilities to enable these decisions. The underlying technology behind transactions, equity offering, and equity share transfers will most likely be the blockchain. Disintermediation and the ability to exchange value, information, and data trustfully without a central authority will enable a new way of funding and cooperation on open-source projects. At the time of the writing and in line with the

Abernathy and Utterback model (Utterback et al. 1975) many players are currently investing and innovating on blockchain to provide services that will satisfy the new market needs.

From this perspective, two different types of companies can and will operate in the market: those which have blockchain at their core since their foundation, and those which have (or will have) to embark in a digital transformation process to reconvert themselves into blockchain-based enterprises. In both cases, companies are investing to get a competitive advantage over competitors, betting on the technology that is promising to reduce costs and increase efficiency. Once a dominant design in product and services will be achieved, companies that took a different path will likely exit the market, letting firms following the dominant design to gain market shares.

To conclude and to conceptualize the insights obtained from both quantitative and qualitative data, four scenarios have been built. The framework revolves around two main dimensions: on one hand the digitization of assets, and on the other hand the change in business models. The proposed framework leads to the identification of four quadrants: scenarios which envision both the digitization of assets and business model changes and scenarios which do not foresee neither of these two changes. These four main development scenarios were completed and analyzed in the light of the conducted interviews and of the quantitative and qualitative data gathered through the Delphi survey. Each quadrant was given a label: Internal Processes, Flow-less Coopetition, Suppliers Potential, and Investment Opportunities. The derived scenarios are not to be considered mutually exclusive. Indeed, they could co-exist in time or also in different geographies.

To the end of this chapter, it is interesting to provide a brief overview of the scenarios, that will be then compared to the investment choices of venture capitalists. The least disruptive scenario, which has been called “Internal

Processes", describe an incremental and not transformational adoption of the technology to improve or automatize internal processes. By reducing the need of a trusted authority, blockchain could simply make smoother processes that today requires a higher level of human involvement. From this perspective, the "Flow-less Coopetition", appears to be an evolution of the first-described scenario. By providing access to data and processes with the highest level of trust, companies will be able to cooperate smoothly, and business models relying on information asymmetry could easily see a sharp decline. This smooth coopetition, involving both competitors and partners, can easily be translated to suppliers as well. From this perspective, and in the scenario called "Suppliers' Potential", two phenomena could be occurring. From one side, traditional suppliers could be more easily integrated in supply chains, leading to a smooth flow of product, services, and financial assets. From the other side, new business-to-business (B2B) blockchain suppliers are likely to see the light. These new businesses will become the suppliers of easy-to-integrate blockchain solutions for companies that do not own in-house competences and skills to build their own blockchain but want to exploit its potential. Eventually, the most disruptive scenario involves both the complete digitization of assets, and the birth of new business models. This scenario revolves mainly on financial aspects: the complete digitization of companies' assets could lead to radically new forms of access to credit and funding. In this scenario, both money-seekers and capital providers (professional, as well as retail investors) could radically change the way in which they operate. Smooth access to trusted information and digitized company assets could open the door to new investment opportunities (in terms of geography, industry, but also level of risk) with a completely new level of capital efficiency.

3.3.2 Where are VCs investing?

As previously highlighted, the scope of this chapter is to investigate whether venture capitalists and industry experts (i.e., the key opinion leaders that were

involved in the Delphi study) agree upon the possible blockchain-enabled future. Building on paragraph 3.2.3 VC investments in blockchain in this section multiple reports on blockchain investments by VCs are explored to get a better understanding on the solutions on which investment professionals are betting.

To this end, it is interesting to look at the top five companies by capital raised active in the blockchain space[10] in 2020. The companies are Bakkt[11], Paxos[12], Chainalysis[13], BlockFi[14], and Bitso[15], which have raised respectively $482,5 millions, $240 millions, $167 millions, $158,7 millions, and $66,4 millions. Four (all except Chainalysis) out of these five companies are active in the financial technology space. However, having a deeper look at their product and service offerings appears to be crucial to reconcile (if possible) those companies with the scenarios built according to the experts involved in the Delphi process. Thus, before moving to discussing whether these companies fit within the scenarios, the following lines dig into more details of the afore mentioned VC-backed start-ups.

3.3.1 Bakkt

Bakkt is a business-to-business financial technology company that offers a variety of services and products to its clients to let them exploit and integrate blockchain solutions in their offering. As per their website, they have developed multiple tools revolving around cryptos that they offer to their clients to engage with consumers in a smart and technological way. To make an example, "Crypto Connect" is their product to allow client's customers to easily buy, sell, and trade cryptocurrencies directly within the client's interface. Always according to their website, they have already partnered with some of the biggest financial institutions

[10] Cointelegraph Consulting Venture Capital Report, 2021
[11] https://bakkt.com/
[12] https://paxos.com/
[13] https://www.chainalysis.com/
[14] https://blockfi.com/
[15] https://bitso.com/

worldwide (Mastercard, to name one) to integrate their solutions. Bakkt, which has gone public in 2021, has been backed by some of the most reputable VCs, such as Microsoft's Venture Fund.

3.3.1 Paxos

Paxos is another business-to-business US-based fintech company that partners with financial institution to provide a platform-as-a-service blockchain settlement solution for capital markets. They have structured their service offering around three main dimensions: custody, digitize, and mobilize. Their objective is to allow their clients (usually big financial institutions) to easily interact with any blockchain. Paxos itself is a regulated financial institution, and has been backed, among the others, by PayPal Ventures, the corporate venture arm of PayPal.

3.3.1 Chainalysis

Chainalysis is the only company among the top-backed that is not purely fintech. Based in the United States, they provide data and analytics to a variety of partners, such as governments agencies and financial institutions. Interestingly to the scope of this research, their business model revolves around reducing information asymmetry in a trusted and decentralized way. The company has been recently financed by Blackstone Group and Accel, two very reputable investors in the space.

3.3.1 BlockFi

BlockFi is a business-to-consumer digital platform that aims at providing retail accounts with crypto-related services for wealth management. Particularly, they have developed a product to allow their customers to get crypto-based loans, thus expanding the possibility to get access to credit for individuals. BlockFi has received funding from Bain Capital Ventures and Tiger Global Management.

3.3.1 Bitso

Bitso is the only company not coming from United States, being based out of Mexico. Bitso is a classical exchange, thus providing a platform to Mexican consumers to trade cryptocurrencies. The companies acknowledge Coatue and Tiger Global Management among its shareholders, thus has been able to convince very reputable investors about its potential.

3.4 Do VCs and experts agree on the blockchain-enabled future?

The previous two sections (namely section 3.3.1 Interpretation of Delphi projectionsand section 3.3.2 Where are VCs investing?) have explored blockchain-enabled futures from two different perspectives: the one coming from industry experts and the one belonging to venture capitalists. The following lines aim to compare the findings previously presented and to drive conclusions on the level of agreement on blockchain-enabled futures.

The following table (Table 19 –) aims to reconcile and compare investment choices of venture capitalists to the scenarios built out of experts' opinions.

Scenario	Description	Degree of Disruption	VC trend
Internal Processes	Companies automate internal processes and make them more efficient thanks to blockchain technological features	**Low** (No digitization of assets, no change in business models)	Among 2020 top invested companies, none focuses on such aspects
Flow-less Coopetition	Thanks to reduction of information asymmetry, companies cooperate in a smoother way, exploring new business models	**Medium** (No digitization of assets, but significant change in business models)	Chainalysis, which raised $167m in 2020 from VCs, focuses on this precise aspect by providing **trusted** data

			and analytics to reduce information gaps
Suppliers Potential	New suppliers are born offering BaaS (Blockchain-as-a-service) solutions to existing incumbents	**Medium** (Digitization of assets, no change in business models)	The two companies which has raised the most by VCs in 2020 (Bakkt and Paxos, accounting for more than $700m in total) embrace this scenario: they are born to provide big enterprises with easy-to-use blockchain-powered solutions.
Investment Opportunities	Digitization of assets, coupled with new business models enable completely new investment opportunities	**High** (Full digitization of assets, disruption in business models)	BlockFi and Bitso were born in complete agreement with this scenario, providing new solutions to retail and professional investors to get access to new forms of investments, that have been enabled by the blockchain adoption

Table 19 – Comparison between Experts' derived scenarios and top blockchain VC-backed companies

Interestingly, all the five top start-ups which have been considered in this research, and which have been raising the most by venture capitalists in 2020, fit very precisely in the scenarios that have been derived out of experts' opinions. Not surprisingly, VCs are focusing their attention on backing companies which are working to enable more disruptive scenarios ("Supplier Potential", "Investment Opportunities"). These two scenarios account for more than 90% of the deployed capital ($956 millions out of $1,114 millions) among the companies in our analysis.

From this perspective, experts and venture capitalists seem to be aligned on how the blockchain-enabled future will look like, with the latter betting on higher-risk (and higher-rewards) scenarios.

3.5 Conclusions

Being the current literature widely fragmented, we believe this research represents a useful starting for conceptualizing blockchain potential and implications. While many research papers focus on blockchain specific applications or general reviews of the state of the art, we try to propose a unifying framework building on different typologies of insights and analyses. We merged quantitative observations derived from standard statistics with qualitative insights obtained directly from experts' opinions and investment trends from venture capitalists.

Overall, we believe our research can constitute a useful tool for many practitioners involved in the innovation ecosystem and for managers of small, medium, and large enterprises to look at future possible scenarios in a more rational and systematic way. From one side, a company's management can use these forecasts as a starting point for the implementation of new strategies. As previously highlighted, blockchain offers endless possibilities. However, the ability to focus on activities and projects with a positive return on investment will be crucial. Firstly, managers will face the choice between insourcing or outsourcing the technological development of the platform. While the former choice ensures higher flexibility, it also generates high development and maintenance costs. Companies which will identify blockchain as their core service will be entitled to adopt this first strategy, while most of the enterprises will probably gain better competitive advantages adopting Blockchain as a Service (BaaS) solution. This latter approach will boost companies' performances, by enhancing new service offerings as well as a new level of operational efficiency, without carrying the burden and costs of technological complexity.

As mentioned, we believe this research provides useful insights for policy makers as well. The adoption of blockchain represents a tremendous technological change bringing along interesting and tangible opportunities. However, different threats can be foreseen. Central authorities do not only solve the problem of trust in certifying value transactions. They also provide essential supervision on the process itself, for example ensuring that information asymmetry is kept at reasonable levels between parties engaging in any sort of contracts, especially in the financial world. Letting people directly exchange value between themselves or allowing companies to easily raise capitals can boost financial efficiency, but also provides room for frauds and ambiguous behaviors. Today, companies which are interested in raising capitals both through innovative tools such as crowdfunding or through traditional entities such as public financial markets, have the duty to disclose relevant information and usually go through a deep process of due diligence. Regulators should ensure the same level of control on companies that will raise money through Initial Coin Offerings or other sort of blockchain-enabled offerings. We believe that the first step towards a fair regulation of this newly born technology is the understanding of its foreseeable impact on the society soon. This work aims to be a precious enabler in this direction. As highlighted in the body of this research, it appears fundamental for policy makers, regulators and government to deeply understand the potential upsides and threats of this new technology, and to correctly navigate the different possible blockchain-enabled scenarios. The successful cooperation between companies' management and regulators could enable significant productivity shifts in the economic tissue of many countries. Failing in efficiently grasping and enhancing these new paradigms from a regulatory perspective could result into a heavy deficit for the competitive edge and productivity of the industrial sectors of the governments' respective countries, potentially leading to macroeconomic differentials in productivity.

Overall, and building from experts' opinions and venture capitalists' investments, we believe blockchain will play a major role in the society by 2030.

From this perspective, it is clear why venture capitalists are trying to ride this trend by investing huge amount of money in the sector. From one side, the market potential of the technology appears to be huge, and from the other side experts and industry leaders agree on the impact that such technology could have on the lives of billions of people and thousands of businesses, opening the door to VCs for above-the-average returns on their investments. Of course, the risk profile of these investments is incredibly high, being the technology in a liquid and not yet crystallized phase, but is in line with this specific high-risk, high-reward asset class.

Chapter 4

VC, technologies, and market value

4.1 Introduction

As previously mentioned, small teams of investment professionals (often referred to as Venture Capitalists – VCs) are required to select and invest in what they think are the best (i.e., most profitable) startups and technologies. However, VCs are not the only ones required to scout, invest, and develop the most promising technologies: established companies run this process daily within their Research & Development (R&D) departments. It is interesting to investigate the space which lies at the interplay between VCs and established firms in their capabilities of selecting technologies on which they bet money, time, and significant other resources. Although the focus of VCs remains purely financial while established enterprises evaluate strategic aspects as well, the latter are ultimately required to please shareholders from a financial perspective, making them similar to long-term and patient investors such as VCs. Within this work, we aim to build a bridge between listed firms and VCs through the underlining technologies they believe (i.e., they invest) in.

To this aim we start from the seminal work of Hall et al. (2005) and we examine whether investment choices of VCs can be viewed as indirect proxy (i.e., a signal) for the market potential of new technologies, and consequently should be considered an important metric to value intellectual property and the firms owning these intangibles. We empirically test such a hypothesis by using a large sample of enterprises (i.e., made of 1,664 listed companies and 463 VC-backed firms) with

headquarters located in the US and operating in two R&D-intensive sectors: biotechnology and pharmaceuticals. Both industries witnessed a steady growth of VC investments starting from the biotech revolution of the Seventies. Forty years later, the field accounted for more than 1,3 trillion dollars in total economic output, representing nearly 4% of the gross domestic product in the US.

Consistent literature has already been written around the two core topics of this work. Several authors have focused on proposing and explaining valuation techniques for public companies (e.g., Damodaran, 2011; Fernandez, 2007; Kellogg and Charnes, 2000; Schmidlin, 2014), private companies (e.g., Armstrong et al., 2006; Caviggioli et al., 2020; Damodaran, 1999; Feldman, 2005; Gornall and Strebulaev, 2020; Mellen and Evans, 2018; Pinto, 2020), or specific assets, such as intellectual property (e.g., Lagrost et al., 2010; Hall et al., 2005; Hsu et al., 2021; Parr, 2018; Reitzig, 2003; Van Zeebroeck, 2011). Another strand of literature has focused on investigating the VC ecosystem (e.g., Cochrane, 2005; Da Rin et al., 2013; Gompers and Lerner, 2001, 2004; Lerner and Tag, 2013; Manigart and Sapienza, 2017; Zider, 1998) also digging into the relationship between venture capital and public equity markets (Gompers and Lerner, 2004; Gompers et al., 2008; Liu and Tian, 2018). Within this context, our work aims at closing the gap between these two well-developed literature streams. Albeit each body of research is well developed, there is still a gap at the interplay of such areas, and we aim at contributing by building an empirical bridge between listed and private companies based on the technologies they have been developing. Thanks to this approach, we can gain insights on different dimensions. Firstly, we propose a novel empirical model to appraise intellectual property assets and evaluate the perceived potential value based on the investment behavior of VCs. Secondly, we can elaborate on the innovation dynamics in the pharmaceuticals and biotechnology sectors, and, additionally, we investigate if, and to what extent, listed markets incorporate the information on VCs investment activity while pricing public companies and their

assets. To the best of our knowledge, no existing contribution focused on establishing a connection between these two distinct fields of study as far as asset valuation is concerned.

More specifically, we test the hypothesis that the technological proximity of listed companies to VC-backed technologies could be a useful (additional) metric to predict the market value of biotech and pharmaceutical firms that are publicly traded on the major US stock market exchanges. Indeed, we argue that VCs are potentially more effective in selecting the most promising early-stage technologies among the wide pool of solutions developed by scientists because of their specialization, access to private information, and long-term investment perspective. If this hypothesis is empirically confirmed, then listed companies developing a set of technologies that lies closer to the portfolios of VC-backed firms should display a higher market valuation with respect to those businesses associated with a more distant set of patented inventions.

Interestingly, our results suggest the opposite mechanics holds true. One possible explanation for the observed phenomenon could be linked to the specific industries we are analyzing in this work. As the development process for new drugs is particularly long (often requiring more than 10 years from discovery to commercialization), public market operators using standard valuation techniques linked to cash flows projections could have difficult times in incorporating in today's valuations the potential upsides linked to technologies that will become revenues-generating in 10 years (or more) from now.

The remaining of the chapter is organized as follows. Section 4.2 gives a thorough overview of the relevant literature on company and intellectual property valuation, venture capital, and technology distance metrics. Data and methodology are shown in Section 4.3. We provide a comprehensive description of the sample in

Section 4.4. Section 4.5 presents the econometric models used. Finally, we give the concluding remarks, and we show our results in Section 4.6

4.2. Literature review

4.2.1. Company and intellectual property valuation

The relevance, process, and implications of valuing companies and assets have recently attracted a great deal of attention from both the academic community and practitioners. The many studies published on these issues can be traced back to three major streams of literature looking at i) public (i.e., listed) companies, ii) private firms, iii) individual assets (e.g., patents). The ability of markets to correctly price enterprises through the supply and demand mechanisms has been at the core of numerous contributions, including the efficient market hypothesis. Born over fifty years ago in the seminal papers of Fama (1970) and Samuelson (1965), its goal was to understand the role and importance of markets, seen as the interplay between sellers and buyers, as means for appropriately valuing assets under different sets of circumstances linked to the amount of information available for participants. In the strongest form of this model, investors have access to any relevant data (i.e., both public and private) useful to price firms whereas they gradually lose bits of information as the assumptions of the theory are loosened[16]. A major result of the study was that markets were shown to behave rationally under conditions of perfect information, which implies that assets are traded at a price equal to their intrinsic value.

Over the last decades, building on the efficient market hypothesis, scholars and practitioners have proposed a variety of tools and methods, both theoretical end empirical, to describe how market participants value companies in the most correct

[16] In the weakest version of the hypothesis, only past asset prices are made available to the traders, and no additional information.

way highlighting how different drivers (e.g., financial data, macroeconomic factors, markets dynamics) contribute to firms' valuation (e.g., Damodaran, 2011; Fernández, 2007; Kellogg and Charnes, 2000; Schmidlin, 2014). Empirical models describing *ex-post* valuations given micro and macro-economic factors have greatly revealed the dependency of asset prices on a very broad set of variables (e.g., Humpe and Macmillan, 2009; Sirucek, 2012). However, as proxied by the Moore's law on semiconductor capacity (Moore, 1965), technology complexity is increasing exponentially. While companies operating in a variety of R&D-intensive sectors are substantially and increasingly investing in highly complex assets and technologies, the ability of sector-agnostic investors to correctly understand the technologies' potential could be limited. Within this context, a stream of literature has shown how companies which heavily rely on intangible assets tend to be undervalued (Corrado et al., 2009; Crouzet and Eberly, 2019; Edmans, 2011; Ewens et al., 2019; Farre-Mensa et al., 2020; Hegde et al., 2018; Hsu and Ziedonis, 2013). Particularly, among intangible assets, intellectual property is extremely relevant for highly technological firms. From this perspective, a well-nurtured research avenue has investigated how intellectual property assets influence listed firms' valuation.

Of particular interest for the scope of this work is the contribution from Griliches (1981), in which the market value approach has been conceptualized and from which a new research avenue has followed (Hall et al., 2005; Sandner, 2009). The market value approach has been conceived starting from the assumptions that the value of a firm is given by the sum of the values of its assets, both tangibles (equipments, facilities, etc.) and intangibles (R&D expenditures, patents, trademarks, etc.). From this perspective, assessing the contribution of intangible assets to the overall valuation of a company means correctly attributing the overall firm's value to its single assets (both physical and intangible), and then considering intangible assets only. Thus, from the seminal work of Griliches (1981), Hall et al. (2005) have developed a model to investigate whether patents' quality was actively

valued by markets and could be considered as an important metric for intangible assets' valuation. Remarkably, they have confirmed how highly cited patents (supposed to be of higher quality) positively, significantly, and strongly influenced the valuation of firm's owning them. Building on this literature stream, other models have followed, sophisticating the approach to decompose the overall intangible assets value into more granular categories. For example, Sandner (2009) proposed a model to correctly appraise the weight of trademarks within the firms' market value, showing a statistically significant relationship between market value and trademarks. Among the sectors in which firms more heavily rely on intangible assets, the pharmaceutical one is undoubtedly remarkable for at least two main aspects: firstly, because pharmaceutical companies' most valuable assets are indeed patents (Sandner, 2009), and secondly because technology complexity (e.g., gene, cell, or mRNA-based therapies, etc.) has exponentially increased since the biotech revolution started in 1976, when Robert Swanson (an American VC) and Herbert Boyer (an American scientist) founded Genentech, the first biotech company in the world (Hughes, 2011). Due to these reasons, the ability to properly value pharmaceutical intellectual property assets appears to be fundamental to appraise the firms themselves, but, at the same time, sector-agnostic financial operators and analysts could encounter not negligible difficulties in understanding the true potential of the different technologies. Given the described context and the objectives of our research, the pharmaceutical and biotech industries appear to be an ideal setting for the empirical analysis we are willing to conduct. Starting from the foundational work by Hall et al. (2005), many other studies have been conducted to properly assess and value firms' patent portfolios and consequently understand the weight of these technological portfolios within the company valuation also in the pharmaceutical world (Chen and Chang, 2010b,a). Other works have proposed numerous methodologies to correctly understand patents' potential and to correctly price those assets (Hsu et al., 2021; Lagrost et al., 2010; Parr, 2018; Van Zeebroeck,

2011), but without a specific focus on the relationship between market value and the assets under investigation and considering several industries.

4.2.2. Venture capital

VCs provide equity finance to early and late-stage firms which they believe will experience outstanding growth. While theoretically everyone has access to equity of listed companies through stock exchanges, investments in private enterprises are often reserved for professional investors, high net-worth individuals, or they should be mediated by authorized institutions (e.g., equity crowdfunding platforms) in the case of retail investors. The attributes, purposes, and benefits of VC financing have been extensively studied from different perspectives by scholars and practitioners.

Within the literature investigating the main factors that are believed to affect the investment choices of VCs, different studies have investigated the signaling role of patents as a mechanism to reduce information asymmetry and proxy for startup quality (Audretsch et al., 2012; Baum and Silverman, 2004; Conti et al., 2013; Hoenig and Henkel, 2015). This is especially true in the case of sectors that are more reliant on patents for appropriating the returns to R&D (Baum and Silverman, 2004). Indeed, the biotech and pharmaceutical industries are often subject to one-takes-all dynamics, whereby a new patented drug conquers the whole market for a specific indication, leaving no space for competing therapeutic compounds based on similar technologies (Lerner, 1995). Given the higher economic importance of patents relative to other means of protection in the analyzed sectors, IP assets represent a meaningful tool for VCs to identify promising ventures (Baum and Silverman, 2004). We argue that the opposite may also hold true: financing deals can be an effective signal about the quality of startup technology. As VCs carefully evaluate startups' intangible assets, their investment could be a strong signal of the underlying technology. Among the most relevant studies, Häussler et al. (2012)

have highlighted the signaling role of patents to attract venture capital in the presence of asymmetric information. Mann et al. (2007) have investigated the relationship between the patenting behavior of software startups and their likelihood to grow into more mature corporations thanks to capital inflows from VCs. Hoenig et al. (2015) have focused on the role of intellectual property as one of the key drivers in attracting substantial capital. Interestingly, Zhang et al. (2019) have concentrated on the signaling power of patents for VCs operating in the bio-pharmaceutical space in China. They have argued that patents contribute to attract venture capital financing by means of three different types of signals: technological, commercial, and legal. By using an empirical approach, they have shown how legal and technological signals of patents have the highest impact on the likelihood of rising capitals. Their findings contribute to supporting the underlying hypothesis of this work, which we believe holds true especially in technology-driven sectors such as the pharmaceutical and biotechnology ones: in a context in which information asymmetry is very high, venture capitalists try to gather information from the few sources at their disposal, among which patents represent a fundamental pillar.

Another literature stream to which this work contributes to has focused on the peculiar valuation process followed by VCs (e.g., Armstrong et al., 2006; Caviggioli et al., 2020; Damodaran, 1999; Feldman, 2005; Gornall and Strebulaev, 2020; Mellen and Evans, 2018; Pinto, 2020). Indeed, despite both VCs and public market financial operators are required to value assets and firms while investing the capital they manage, they follow peculiar and distinct decision-making processes (Gompers et al., 2020; Scharfstein and Stein, 1990). A large and heterogeneous pool of sector-agnostic investors regularly trades on public markets whereas VC teams often specialize around few sectors, developing vertical industry knowledge (Gompers et al., 2005, 2009). We argue that these specific characteristics could represent a competitive edge for VCs while assessing highly complex technologies such as the ones being developed by bio-pharmaceutical companies.

4.2.3. Technological proximity

As discussed by Peretto and Smulders (2002), technological proximity measures are useful in many contexts: i) to assess the distance between individual patents, ii) to relate different fields, and iii) to compare portfolios of inventions. Although these applications are equally relevant, here we focus on the latter only. Note that such methodologies can be employed both at micro and macroeconomic levels to appraise the technological relatedness among inventors, firms, industries, regions, or countries. Since different mathematical formulations have been proposed by scholars and each implementation brings its own peculiarities in terms of characteristics or applicability, they should be carefully selected according to the specific problem of interest. A seminal contribution within this area of research has been the work of Jaffe (1986), who concluded that the reciprocal position of the research programs conducted by firms in the technology space affects systematically their innovative outputs, profits, and market values. Closeness is quantified via the angular separation between the technology portfolios for each pair of companies. Whilst more sophisticated measures have been developed in the subsequent literature for new applications in specific contexts (e.g., Bar and Leiponen, 2012; Kay et al., 2014; Schoen et al., 2012; Stellner, 2015; Vom Stein et al., 2015), this result is noteworthy because it shed light on the relevance of technological proximity for company valuation.

In many instances, well-renowned geometrical concepts – the Euclidean proximity (Benner and Waldfogel, 2008) and Mahalanobis distance (De Maesschalck et al., 2000), the Pearson correlation (Yan and Luo, 2017), the cosine similarity (Jaffe, 1986) – have been successfully applied to the case of technology mapping. Bar and Leiponen (2012) advocated the use of the min-complement proximity to overcome a key limitation of the cosine distance when considering large and very diversified portfolios of inventions, as only relevant technological classes enter the calculation (i.e., those in which the compared firms have at least

one patent). Albeit each different mathematical approach leads to specific benefits and drawbacks, the underlying concept is the same for all the formulations. Indeed, the key challenge is to quantitatively estimate how technologically close are two companies.

4.2.4. Contribution to the extant literature

As widely described in the previous sections, this work lies at the intersection of three well-developed literature streams. Although each of the three streams has been widely investigated by the research community, a link between the fields is still missing. For this reason, and also considering the increasing relevance of VC investments in deep technological ventures (the so called "Deep Tech"), it appears relevant to investigate the space that sits at the interplay of technology, VC investments and financial markets. Thanks to the proprietary dataset that will be presented in the following section, it has been possible to build, and quantitatively analyze, the relationship between VC-backed and listed companies. The underlying technologies under development constitute the bridge between these two separate but tightly correlated worlds. This bridging capability is what the work can add to the aforementioned literature and, to the best of our knowledge, represents the novelty of the research. To give more context, while many works have focused on investigating the technologies invested by VCs, and many others have been describing the R&D efforts of big listed corporations, none has tried to build a link between these two worlds using technologies as the matching key. Thanks to our dataset, not only we have been able to build this link, but we also have moved a step further by including financial considerations into the equation.

4.3. Data and methodology

The empirical analysis described in this chapter relies on a dataset built from a combination of multiple sources. The initial sample was selected using a four-step

approach. We first collected information on both VC-backed firms and listed companies with headquarters in the US and operating in either the biotech or pharmaceutical sectors. Structured data on all investment rounds made in the years from 2000 to 2019 and involving private VC-backed firms (more than 2,000 companies and 8,000 rounds) have been extracted from Preqin[17] and complemented with information about the related investors, advisors, and fund performances (e.g., IRR and multiples, etc.). We gathered from Datastream[18] the list of more than 580 companies listed on the major stock exchanges in the US (i.e., NYSE and NASDAQ) that are operating in the selected industries. Income statements, stock prices, and other financial data have been assembled for each business by means of the corresponding ticker code via publicly accessible APIs[19].

Secondly, we reconstructed several characteristics of the technological portfolios owned by all the companies in our sample using bibliometric data that is available in patent documents. To this end, we retrieved all granted patents between 1976 and 2020 at the United States Patent and Trademark Office (USPTO) by either VC-backed firms or listed companies through the use of the PatentsView database[20]. Patent data has subsequently been associated to each organization name through a fuzzy-matching procedure based on the Levenshtein distance (Yujian and Bo, 2007). To ensure the highest quality of the sample, we manually checked all the matches and corrected algorithmically generated mismatches by manually associating firms to their USPTO identification number. The final sample includes

[17] Preqin provides financial data and information on the alternative assets market.

[18] Datastream is a global financial and macroeconomic platform, providing data on equities, stock market indices, currencies, company fundamentals, fixed income securities, and key economic indicators for 175 countries and 60 markets.

[19] APIs (Application programming interfaces) are interfaces which facilitate the exchange of data between a client and a provider, often through the use of specific algorithms and programming languages

[20] PatentsView is a platform curated by Office of the Chief Economist at the U.S. Patent & Trademark Office (USPTO) which allows to access data on patents applications and grants from the U.S. Patent & Trademark Office.

1,664 VC-backed firms, corresponding to 6,145 financing rounds and 463 listed companies with complete financial and technological data.

We exploited the International Patent Classification (IPC) fields attached to patent documents for measuring the specialization of VC-backed firms and comparing it to that of listed companies in our data. Accordingly, we built vectors having distinct technological sectors as their components and the corresponding patent counts associated with those areas as their values. We then assessed the technological proximity between the aggregate portfolio of patents filed by VC-backed firms together and that owned by each listed company. We operationalize this notion using the standard Euclidean algorithm (Benner and Waldfogel, 2008) which provides the shortest distance computed between two points that are located in an n-dimensional vector space[21]:

$$ED_{it} = \sqrt{\sum_{j} \left(s_{ijt}^{L} - s_{jt-1}^{F}\right)^{2}}$$

where s_{ijt}^{L} is the share of technological fields belonging to category j in the patents owned by listed company i having application year equal to t. Likewise, s_{jt-1}^{F} is the corresponding proportion obtained by using the aggregate set of inventions filed by all VC-backed firms one year prior to t. High values of ED_{it} indicate that the portfolio of technologies developed by the focal listed company i over the period t is very different from the bundle of solutions patented the year before by all the ventures that received funding by VCs and vice versa. Theoretically, such an index can vary from zero to one[22]. We opted for employing shares instead of absolute

[21] Note that n is a positive integer representing the number of distinct technological fields, indexed with subscript j. We take into consideration all the IPC categories at the levels of either subclasses or groups (i.e., codes at four or eight digits, respectively).

[22] However, because we are using relative frequencies under the constraint that each set of patents has at least a size equal to one, the maximum distance is reached when both vectors are characterized

frequencies since biases due to differences in the size of companies are likely alleviated.

We also test the robustness of econometric results with other indicators of technological proximity. The first alternative measure is the angular separation that has been originally proposed by Jaffe (1986, 1989):

$$\mathrm{AD_{it}} = 1 - \frac{\sum_j s^L_{ijt}\, s^F_{jt-1}}{\sqrt{\left(\sum_j {s^L_{ijt}}^2\right)\left(\sum_j {s^F_{jt-1}}^2\right)}}$$

Note that $\mathrm{AD_{it}}$ is here defined as one minus the cosine of the angle between the vectors s^L_{ijt} and s^F_{jt-1}. Given that our computations are based on normalized patent counts (i.e., proportions), the ranking criterion obtained with such an algorithm is equivalent to that generated by using ED_{it}. A different formulation has been developed by Bar and Leiponen (2012) to overcome some known weaknesses of traditional proximity metrics. In particular, the min-complement distance is a function that does not depend on irrelevant technology categories, meaning that only the sectors found in both portfolios of compared patents are taken into account:

$$\mathrm{CD_{it}} = 1 - \sum\nolimits_{\mathrm{j}} \min\left\{\mathrm{s^L_{ijt}}, \mathrm{s^F_{jt-1}}\right\}$$

4.4. Description of the sample

In this section, we illustrate several characteristics of the data. We focus on three main dimensions of analysis: i) the key features of the VC-backed firms, ii)

by the presence of a different component with unitary value. In this circumstance, the result before normalization is $\sqrt{2}$.

the financial metrics of listed companies, and iii) the portfolio of patented technologies filed by both types of enterprises.

The final sample includes 1,664 VC-backed firms, which altogether raised more than 113,78 billion dollars via 6,145 financing deals occurred in the years from 2000 to 2019. The mean and median deal sizes are respectively 18.52 and 9.20 million dollars. Figures 1a and 1b compare the distributions of investments in the pharmaceutical and biotech sectors respectively, with the latter being more asymmetrical and characterized by a larger median value than the former. While 57.0% of the startups raised a total funding amount equal or less than 50 million dollars, only 3.4% raised at least 250 million dollars. Such patterns seem to be in line with the experimental evidence on the startup ecosystem and confirm that the distribution of investments by VC-backed firms is highly skewed: many ventures have sprung up in recent years, but few are good enough to grow and collect significant capital. Indeed, the analysis on the number of deals confirms this hypothesis (Figure 9, 10).

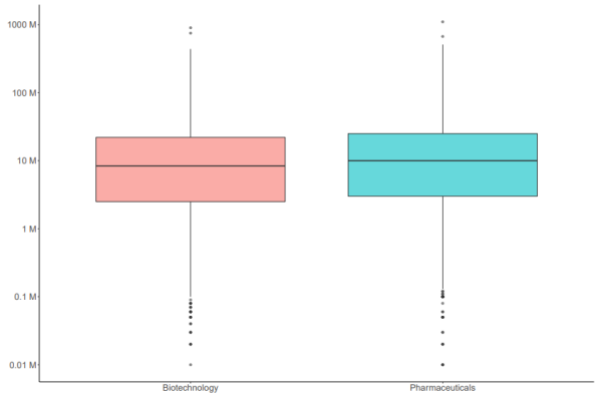


Figure 4 - Distribution of investments deals by sector

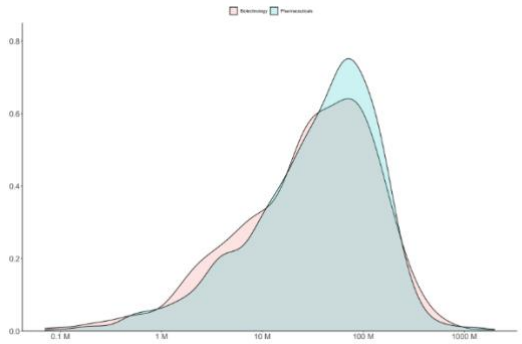


Figure 5 - Kernel density estimation of the total funding amount (in logarithms) by sector

The average company in our sample has raised 3.7 investment rounds for a total amount of 68.5 million dollars, with only 29.3% of the startups closing 5 or more deals. Finally, the 10 most funded VC-backed firms collected 9.6 billion dollars or 8.4% of the total amount raised[23]. In line with these figures, the distribution of the number of investments across the different stages is highly skewed in favor of early-stage rounds. Another interesting dimension to explore is the geographical one. As

[23] They include Grail Inc. (a cancer testing startup backed by Jeff Bezos), Intarcia Therapeutics Inc., Hyperion Therapeutics Inc., Aduro Biotech Inc., Clovis Oncology Inc., and others.

expected, the internationally renowned areas of Boston and San Francisco received the highest number of investments (Figure 7).

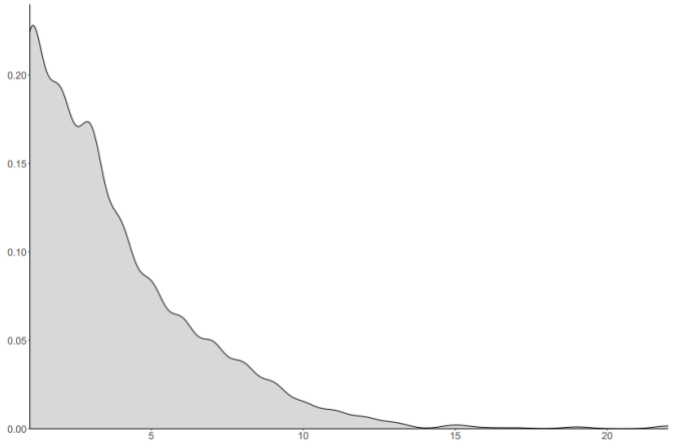


Figure 6 - Kernel density estimation of the deal count by firm

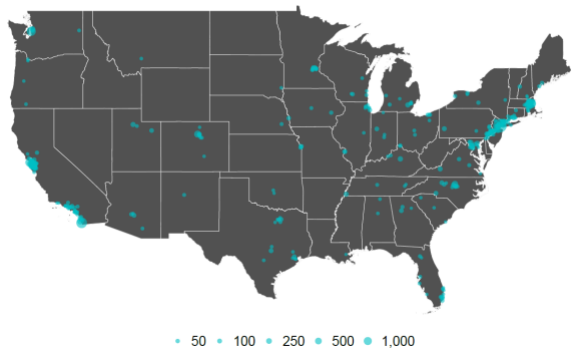


Figure 7 – Geographical distribution of companies in the sample

The second relevant unit of study is listed companies. We identified in our sample 463 enterprises traded either on the NYSE or NASDAQ markets and operating in the biotech and pharmaceuticals sectors. Figure 4 reports the two distributions of market returns (in logarithms) by stock exchange. Another interesting dimension of the sample is given by the distribution of the average size of the firms over the period considered (proxied by the total assets as declared in

their balance sheets). As expected, the enterprises' sizes are not distributed normally, with the mean size of the enterprises in our sample being almost 2 billion dollars. The last set of descriptive statistics is related to patent data. Both VC-backed companies and listed enterprises develop new technological solutions which are being protected through patents. From this perspective, it is interesting to underline few characteristics of the patents' portfolios of the firms in our sample. VC-backed companies have been associated with around 30,000 patents, while listed companies, even though they represent a significantly smaller portion of the sample, account for more than 40,000 patents. This observation confirms that listed companies tend to be bigger, and to have significantly larger patent portfolios. Our average VC-backed firm has about 18 patents in its technological portfolio, while the average listed enterprise has more than 80. We furthermore attached more than 700,000 citations to the 65,457 patents in our sample. As expected, and broadly anticipated by the literature, the distribution of received citations is highly skewed: top 1,000 patents by citations in our sample account for the majority of the total citations received by patents in our sample.

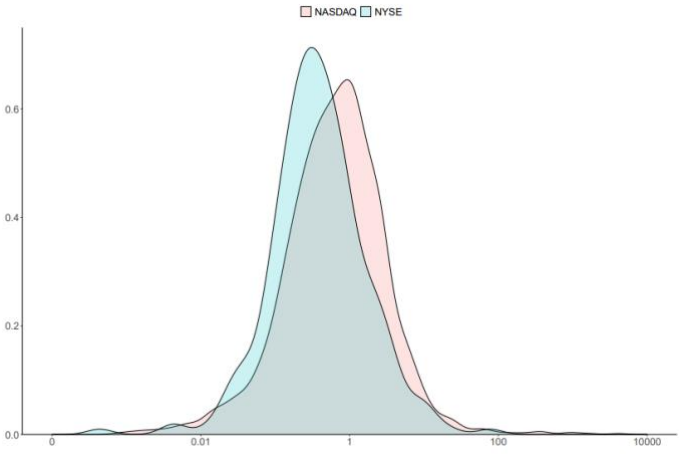


Figure 8 - Distributions of stock market returns by stock exchange

4.5. Econometric analysis

We employ a multivariate regression framework to analyze the relationship between the financial performance of listed companies and their technological proximity to patents filed by VC-backed firms. We start from the seminal work by Griliches, Z. (1981). The authors conceptualized firms' market value (V_{it}) as a function (q_{it}) of both physical (A_{it}) and knowledge (K_{it}) assets.

$$V_{it} = q_{it}(A_{it} + K_{it}) \quad (1)$$

In this representation, q_{it} represents the coefficient through which market decode the value of the assets of the company. It implicitly incorporates the information on multiple aspects, such as the position of the firm within the market (monopoly, oligopoly, …) and of risks related to the company business and its operations. These multiple relationships can be made explicit considering different factors which contribute to the overall valorization function q_{it}, as described by the following expression.

$$q_{it} = e^{m_i + d_t + u_{it}} \longrightarrow \ln[q_{it}] = m_i + d_t + u_{it} \quad (2)$$

From this perspective, three main factors influence the way in which markets value the assets of a firm: a firm-specific, a market-specific, and an error factor. Looking back to equation (1) and (2), and considering Tobin's Q definition, Griliches, Z. (1981) has derived the following expressions.

$$Q_{it} = \frac{V_{it}}{A_{it}} \longrightarrow \ln[Q_{it}] = \ln\left[\frac{V_{it}}{A_{it}}\right] \longrightarrow \ln[Q_{it}] = \ln[V_{it}] - \ln[A_{it}]$$

$$\ln[Q_{it}] = \ln[q_{it}(A_{it} + K_{it})] - \ln[A_{it}] \longrightarrow \ln[Q_{it}]$$
$$= \ln[q_{it}] + \ln[A_{it} + K_{it}] - \ln[A_{it}]$$

$$\ln[Q_{it}] = m_i + d_t + \ln\left[\frac{A_{it}+K_{it}}{A_{it}}\right] + u_{it} = m_i + d_t + \ln\left[1 + \frac{K_{it}}{A_{it}}\right] + u_{it} \quad (3)$$

Staring from equation (3) and using a common mathematical approximation (4), it is possible to derive a first estimating equation characterizing a model linking firms' market value to firms' assets, as detailed in equation (5).

$$\ln[1 + x] \cong x \quad (4)$$

$$\ln[Q_{it}] = m_i + d_t + \frac{K_{it}}{A_{it}} + u_{it} \quad (5)$$

Starting from the model described in equation (5), different authors have proposed other specifications to include additional factors as regressors to explain firms' market value. In particular, and functional to the scope of this work, Hall et al. (2005), and Sandner et al. (2011) have made meaningful contributions. The first have developed a model linking the value of a firm to different kind of assets, including intellectual property assets, leading to a cornerstone estimating equation (6). In this expression, the authors have tried to conceptualize how R&D expenditure, patents, and patents' quality (measured by received citations) can provide a way to meaningfully quantify the knowledge assets of a company.

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = (\sigma - 1)\ln[A_{it}] + \sigma \ln\left[1 + \gamma_1 \frac{R\&D_{it}}{A_{it}} + \gamma_2 \frac{P_{it}}{R\&D_{it}} + \gamma_3 \frac{FC_{it}}{P_{it}}\right] + m_l + d_t + u_{it} \quad (6)$$

In this model, $R\&D_{it}$ represent the stock of R&D expenditure, P_{it} and FC_{it} represent respectively the stock of granted patents and the stock of forward citations for the patent portfolio of company *i* at time *t.* Hall et al. (2005), using a large sample of firms belonging to different sectors, found all these variables to be significantly explaining firms' market value. The stock of the variables in the previous estimating equations are to be evaluated considering the following equations, being δ and g the depreciation and growth rate respectively:

$$R\&D_0^{stock} = \left(\frac{1}{\delta + g}\right) R\&D_0^{flow}$$

$$P_0^{stock} = \left(\frac{1}{\delta + g}\right) P_0^{flow}$$

$$FC_0^{stock} = \left(\frac{1}{\delta + g}\right) FC_0^{flow}$$

$$R\&D_t^{stock} = R\&D_t^{flow} + (1 - \delta) R\&D_{t-1}^{stock}$$

$$P_t^{stock} = P_t^{flow} + (1 - \delta) P_{t-1}^{stock}$$

$$FC_t^{stock} = FC_t^{flow} + (1 - \delta) FC_{t-1}^{stock}$$

Interestingly, Sandner et al. (2011) have further expanded the two models proposed above working on a different specification to include the value of trademarks in the equation. Although in this work we do not focus on trademarks as a signal for market valuation, the work of Sandner et al. (2011) provides a meaningful example

on possible way to enriching the previous models (Griliches Z., 1981; Hall et al.; 2005) with original contributions. They started from the following assumptions:

$$V_{it}(A_{it}, K_{it}) = q_{it}(A_{it}, \gamma K_{it})^{\sigma}$$

With:

$$q_{it} = e^{y_t + c_k + m_l + u_{it}}$$

In the previous equation, V_{it} represents the value of company i at time t, A_{it} its physical assets, K_{it} its knowledge assets and q_{it}, as previously stated, the valuation coefficient of company assets. The valuation coefficient considers an individual disturbance (u_{it}), an industry-specific component (m_l), a time-specific component (y_t), and a country-specific component (c_k). The sigma coefficient represent return to scale. If $\sigma > 1$ the industry is characterized by economy of scale, if $\sigma = 1$ no return to scale can be observed. The latest parameter, γ, is the shadow value of knowledge assets versus physical assets and γq_{it} represent the absolute shadow value reflecting the expectations of investors over those assets. Originally, they included trademarks (M_{it}) in the equations and followed the same logical and mathematical steps already described above, to get to the estimating equations (7) and (8).

$$V_{it}(A_{it}, K_{it}, M_{it}) = q_{it}(A_{it} + \gamma_k K_{it} + \gamma_M M_{it})^{\sigma}$$

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = \ln[q_{it}] - \ln[A_{it}] + \sigma \ln\left[A_{it}\left(1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}}\right)\right]$$

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = \ln[q_{it}] - \ln[A_{it}] + \sigma \ln[A_{it}] + \sigma \ln\left[1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}}\right]$$

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = \ln[q_{it}] + (\sigma - 1)\ln[A_{it}] + \sigma \ln\left[1 + \gamma_K \frac{K_{it}}{A_{it}} + \gamma_M \frac{M_{it}}{A_{it}}\right] (7)$$

As before, $\ln\left[\frac{V_{it}}{A_{it}}\right]$ represents the logarithm of the ratio between the market value of a company to its physical value (Tobin's q). Considering equation (6) and (7), the following estimating equation have been derived.

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = \ln[q_{it}] + (\sigma - 1)\ln[A_{it}] + \sigma \ln\left[1 + \gamma_1 \frac{R\&D_{it}}{A_{it}} + \gamma_2 \frac{P_{it}}{R\&D_{it}} + \gamma_3 \frac{FC_{it}}{P_{it}} + \gamma_4 \frac{TM_{it}}{MA_{it}}\right] (8)$$

4.5.1. Baseline Model

We start by using the specification in Sandner and Block (2011), omitting the trademarks and considering the additional term capturing the technological distance between the listed company and the vector of technologies invested by VCs at time *t*. We assume that no returns to scale can be observed, and we use the already described mathematical approximation (eq. 4) to linearize the model. Starting from equation (8) we derive equation (9), which is our estimating equation. Table 20 and 21 reports the detailed description of the variables used in the model and the relative descriptive statistics. The equation is estimated using a fixed effects model.

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = (\sigma - 1)\ln[A_{it}] + \sigma \ln\left[1 + \gamma_1 \frac{R_{it}}{A_{it}} + \gamma_2 \frac{P_{it}}{R_{it}} + \gamma_3 \frac{FC_{it}}{P_{it}} + \gamma_4 TD_{it}\right] + m_l + d_t + u_{it}$$

$$\ln\left[\frac{V_{it}}{A_{it}}\right] = 1 + \gamma_1 \frac{R\&D_{it}}{A_{it}} + \gamma_2 \frac{P_{it}}{R\&D_{it}} + \gamma_3 \frac{FC_{it}}{P_{it}} + \gamma_4 TD_{it} + m_l + d_t + u_{it} (9)$$

Variable	Description
V_{it}	value of company i at time t
A_{it}	market value of the physical assets of company i at time t
m_l	industry-specific dummy (pharma versus biotech dummy)
d_t	time-specific dummies
u_{it}	individual disturbance
$R\&D_{it}$	stock of R&D performed by company *i* at time *t*
P_{it}	stock of patents of company *i* at time *t*
FC_{it}	stock of forward citations received by patents of company *i* at time *t*
TD_{it}	technological distance computed between the portfolio of patents filed by listed company *i* in year t and the aggregate portfolio of patents filed by all VC-backed firms

Table 20 - Description of the main variables used in the regression model

Descriptive statistics						
	Obs	**Mean**	**Median**	**Standard deviation**	**Min**	**Max**
Tobin's q	3219	2.995	2.471	1.794	0.827	8.548
Total assets (dollars)	3219	3.071.331	89.816	15.744.530	0.004	195.014.000
Logarithm of Tobin's q	3219	0.927	0.905	0.585	-0.190	2.146
Logarithm of total assets	3219	4.659	4.498	2.127	-5.518	12.181
Stock of research and development expenses (dollars)	3219	1.109.834	105.551	5.284.810	0.000	57.438.260
Stock of patents	3219	41.415	3.861	180.373	0.000	2.117.418
Stock of received citations	3219	511.297	6.550	2.354.904	0.000	26.479.363
Research and development expenses to total assets	3219	1.760	1.093	2.289	0.000	26.071
Patents to research and development expenses	3219	0.081	0.033	0.127	0.000	1.105
Received citations to patents	3219	7.618	1.258	27.806	0.000	743.373
Euclidean distance (stock)	2282	0.277	0.247	0.135	0.062	0.723
Angular distance (stock)	2282	0.488	0.460	0.276	0.063	1.000
Min-complement distance (stock)	2282	0.738	0.737	0.143	0.337	1.000

Table 21 - Descriptive statistics of regression variables

4.6. Results and conclusions

Our findings contribute to the extant literature by building a technological bridge between listed companies and their private counterpart. We aim at providing a better understanding on the mechanics which lie behind intangible assets' valuation and their impact on firms' market value, by investigating the relationship between listed firms and startups operating in the pharmaceutical and biotech industries. As reported in Table 22, we preliminary found a positive and statistically significant relationship between listed firms' market value and the technological distance calculated using the Euclidean distance approach. Assuming VCs are usually investing in newly born and innovative approaches, this observation seems suggesting that public markets tend to attribute more value to more mature technologies, highlighting a risk-adverse behavior of public markets participants. This observation is not surprising. Considering standard valuation methodologies based on cash flow projections and considering the long development time needed to bring pharmaceutical and biotechnology products to the market, it appears clear that the value of newly discovered drugs is very difficult to be incorporated in listed firms' valuation. Our results are robust also considering other technological distance specifications, such as the min-complement one, as reported in Table 23.

As previously mentioned, the scope of this chapter has been to understand whether financial markets and venture capitalists value the same technologies. From the empirical analysis conducted, the opposite seems to hold true, as listed companies developing more mature technologies receive higher valuations in the market. However, this observation is not coming as a complete surprise. Listed companies are asked to financially reward their shareholders, and very often are valued based on the financial results they can deliver every quarter. Given the nature of venture capital investments, which are often long-term bets (as, for example, the ones described for blockchain-based startups in Chapter 3), short-term

financial results are difficult to achieve by investing in technologies which are still in their early development phases.

Baseline models		
Dependent Variable: **Firms' Tobin's Q**		
	Model 1	**Model 2**
Research and development expenses to total assets	0.039***	0.042***
	(0.007)	(0.009)
Patents to research and development expenses	0.271	0.516**
	(0.217)	(0.259)
Received citations to patents	0.001	-0.002
	(0.001)	(0.001)
Euclidean distance (stock)		0.414*
		(0.224)
Dummy year	Yes	Yes
Observations	3219	2282
Rho	0.419	0.452

Table 22 - Baseline models

Robustness models			
Dependent Variable: **Firms' Tobin's Q**			
	Model 1	**Model 2**	**Model 3**
Research and development expenses to total assets	0.042***	0.042***	0.043***
	(0.009)	(0.009)	(0.009)
Patents to research and development expenses	0.516**	0.491*	0.559**
	(0.259)	(0.257)	(0.255)
Past received citations to patents	-0.002	-0.001	-0.001
	(0.001)	(0.002)	(0.001)
Euclidean distance	0.414*		
	(0.224)		
Angular distance		0.246	
		(0.152)	
Min-complement distance			0.711**
			(0.318)
Dummy Year	Yes	Yes	Yes

Observations	2282	2282	2282
Rho	0.452	0.454	0.467

Table 23 - Robustness check using different technological distance measures

Chapter 5

Final Remarks

This chapter constitutes the final section of this thesis. Across the three main chapters of this work, the two fundamental questions highlighted in the introductory section have been addressed, leading to a better understanding of the VC phenomenon from multiple perspectives.

We believe it is now clear that social impact of venture capital investments is becoming a must-to-consider aspect for investment teams. Different social impact dimensions have been explored and, using quantitative and empirical methodologies, the short- and long-term financial impacts of social impact venture investments have been highlighted. Thanks to the empirical analysis, from one side it was possible to highlight specific features of the social impact venture capital investment process, and, from the other side it was possible to quantitatively evaluate the positive long-term effect of VCs on the invested social impact companies. It is now clear that assessing, measuring, and boosting the social impact of VC investments are key aspects that are already being considered by investment teams and that will have a central role in the upcoming years.

Having answered the first question (i.e., do VCs care about the social impact of their investments) the second and third chapter of the thesis focused on understanding if VC investment teams focus on relevant and promising technologies. To address the topic, two different perspectives and two different methodologies have been used. Given the wide spectrum of technologies and start-ups which daily receive VC investments, it has firstly been necessary to restrict the research focus to a bunch of specific sectors, namely the blockchain and

biotechnology ones. The two sectors have been chosen as exemplifying the whole VC phenomenon given the recent and growing trend of investments that the two sectors have been receiving over the last few years (accounting for more than $50b in 2021 alone). Firstly, it was interesting to convey structured feedback from an heterogenous pool of expert on the outlook of blockchain technology and its possible impact on our society, and then compare it with VC investment trends in blockchain-based ventures. It is now clear that there is a substantial alignment between VCs and experts on the endless possibilities that blockchain technology can enable. At the same time, key opinion leaders highlighted how the technology is still in a fluid phase, with no design neither application already consolidated to be dominant in the new paradigm that is being created. The merge of these two considerations is coherent with the whole VC *modus operandi,* that should select high-risk but high-reward ventures before their value becomes clear to the most. Interestingly, and moving to the last dimension explored in this work, the scenario is quite different for the biopharma sector. By comparing public (i.e., listed) firms to VC-backed start-ups using a proprietary technology-based database, it appeared evident that financial markets (which everything knows, at least theoretically) tend to give a premium on more mature technologies, rather than betting on new disruptive and innovative solutions. While this finding could sound counter-intuitive, as VCs should be selecting the best technologies out of the crowd, it strengthens the assumption that venture capitalists really select and invest in long-term, high-risk projects. Those projects, especially in the biopharmaceutical sector, are very far from generating any profit, and a huge development risk is still associated to those technologies at the time VCs pick them as their bet. Thus, the lower value assigned by financially driven public markets, which are built to reward companies that provide consistent returns to their shareholders.

Overall, and considering the different chapters and findings altogether, the picture that emerges from the whole thesis is quite promising. Venture capitalists care (and will care even more in the future) about the social impact of their

investments and provide value to those companies as well. They select technologies that experts consider having a great potential, and do not care about short-term financial considerations, but bet on long-term high-risk high-rewards projects that have the potential to radically change (for the better) our society.

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