INSTITUTO
UNIVERSITÁRIO
DE LISBOA

The main drivers of Venture Capital investment in the European Fintech Ecosystem

Tiago Pejapes Coutinho

Master in Finance

Supervisor:
PhD Rui Manuel Meireles dos Anjos Alpalhão, Invited Full Professor,
ISCTE-IUL

September 2023

BUSINESS
SCHOOL

Department of Finance

The main drivers of Venture Capital investment in the European Fintech Ecosystem

Tiago Pejapes Coutinho

Master in Finance

Supervisor:
PhD Rui Manuel Meireles dos Anjos Alpalhão, Invited Full Professor,
ISCTE-IUL

September 2023

Acknowledgments

The conclusion of this thesis marks the end of my journey as a student in this master's program. Hence, I would like to use this chapter as a reflection of this journey and appreciate all the support I have received until now.

To my family, know that I aspotm forever grateful for everything that was given to me. All the support that you have provided me since I was born is remarkable and I'll always be in debt to you. I truly hope to capture all the guidance and moral codes that you have shown me and do a similar job for future generations. To my mother, there is no greater role model that I know of that impersonates the word "sacrifice". To my father, thank you for showing me every day what true professionalism is, as well as challenging me every day to live up to the highest standards. To my brother, thank you for also being a great role model in never giving up.

To the rest of my family, thank you for always caring for me and providing me with your full support daily. I feel blessed to live with all of you.

To my dear friends, I truly and dearly want to highlight how lucky I feel to share a special bond with you. Even though I still see myself as a very young person whose life is just starting, I am grateful to have you all on my side. All the experiences and stories that I have lived and shared with you are, for me, one of the greatest treasures that I hold. I truly appreciate all the orientations, motivations, and challenges that you have given me when I needed them, I wouldn't be as happy with my life if it weren't also for you.

To all my colleagues and professors at ISCTE, I hope that you know that I see you more than that. To my colleagues, I feel that these past two years were my best years academically and socially. That would be impossible without you, so, for that reason, I would like to thank you. I want to extend my special recognition to two colleagues of mine, Radu Cebotari and Duarte Pereira, for the invaluable assistance that they provided me. This project probably wouldn't have been completed without their support. To the professors, I see you also as mentors who take joy in teaching us students to be the best versions we can be. I honestly appreciate you for that and I hope to remain in contact with you.

To the coordinator of this research, Professor Rui Alpalhão, I would like to dedicate this paragraph to you. Thank you for being a great role model for me, offering assistance and direction throughout all steps of this research. The development of this research definitely wouldn’t be possible without you, all your knowledge and expertise of the Venture Capital market, and your guidance.

Finally, to everyone who ever supported me and wasn’t cited above, know too that I am forever grateful for you.

Abstract

The Fintech industry has been attracting massive attention from private investors, mainly Venture Capital, over the last years, due to the great financial returns that previous investments in the sector have generated and, more importantly, how the technology created by this ecosystem can innovate the daily life of society, both socially and professionally. In this thesis, I analyze what are the main drivers of the Venture Capital industry's investment in the European Fintech sector. My objective with the research is to determine how this new market is being developed by Venture Capitalists and what are the main drivers of the demand for this new technology. Upon that, I aggregated and examined the investments that were made by VCs in European Fintech start-ups during the period 2018 – 2021, using the Crunchbase database. I initially performed descriptive statistics to achieve an overview of the market. I used econometric models to conclude what were the possible main variables that influence the relationship between the two sectors. I'll use as explanatory variables the amount and stage of the investment, the start-up's location, age, composition of the team, and industry, and the VC's age, location, and investment fund focus.

Keywords: Fintech, Venture Capital, Europe, Investment, Start-up

JEL Classification: G11, G20, G24

Resumo

A indústria de Fintech tem atraído grande atenção por parte de investidores privados, nomeadamente Venture Capital, nos últimos anos, devido a grandes lucros financeiros que investimentos prévios no setor capturaram e, mais importante ainda, como a tecnologia criada pelo ecossistema consegue inovar o dia a dia da sociedade, quer socialmente como profissionalmente. Nesta tese, investigo quais as maiores variáveis que influenciam o investimento no setor europeu de Fintech por parte da indústria de Venture Capital. O meu objetivo com esta investigação é descobrir como este novo mercado está a ser desenvolvido por VCs e quais são as principais causas da procura por esta nova tenologia. Tendo isto em conta, eu reuni e analisei os investimentos que foram feitos pela indústria VC em start-ups europeias de Fintech durante o período 2018 – 2021, através da base de dados Crunchbase. Comecei a análise com estatística descritiva, de forma a obter uma avaliação geral do mercado. Usei modelos econométricos para concluir quais poderiam ser as principais variáveis que influenciassem a relação entre os dois setores. Usei como variáveis independentes o montante e fase do investimento, a localização da start-up, a composição da equipa, indústria, assim como a idade da VC, localização e o foco do fundo de investimento.

Palavras-chave: Fintech, Venture Capital, Europa, Investimento, Start-up

Classificação JEL: G11, G20, G24

Table of Contents

Index of Figures, Tables, and Graphs

FIGURES

TABLES

GRAPHS

Glossary

ATM – Automated Teller Machine

BVC – Banking Venture Capital

BM – Blockchain Marketplace

BI – Business Intelligence

CVC – Corporate Venture Capital

EMEA – Europe, Middle East, and Africa

FINTECH – Financial Technology

FS – Financial Services

FM – Financial Markets

GDP – Gross Domestic Product

GP – General Partner

GVC – Government Venture Capital

IPO – Initial Public Offering

ICO - Initial Coin Offering

IT – Information Technology

IVC – Institutional Venture Capital

LN – Logarithmic Scale

LP - Limited Partnerships

M&A – Mergers and Acquisitions

MLRM – Multiple Linear Regression Model

P2P – Peer-to-peer

PE – Private Equity

OLS – Ordinary Least Squares

SaaS – Software-as-a-Service

SME - Small and Medium Enterprises

SWIFT - Society for Worldwide Interbank Financial Telecommunication

VC – Venture Capital

1. Introduction

Ever since modern society has looked at knowledge as a path to improve one's well-being, innovation has been the greater goal of all. The path to innovation has not only improved past industries', but also disrupted some in the creation of new ones.

But why was this use of technology so needed in the financial industry?

For us to answer that question, we need to rewind in time. Ever since the 2008 financial crisis broke out and negatively influenced society, the trust that individuals had in the financial system was split into pieces. There was an urgent need for a change in the financial system that was still to be applied. Technology was just that change. Technology created automated platforms that minimize (or completely eliminate) human risk in financial transactions. Instead of these operations being done by operators (for example, a broker) the institutional firm could use an algorithm that chose the best deals to invest in.

The use of technology in the financial system wasn't exactly new, there were already some financial instruments that required technology in order to operate (SWIFT messages, for example). However, this resource wasn't heavily applied to the banking system and there were essential sectors in the financial system that didn't account for any presence of technological instruments (for example, the due diligence or the KYC sectors).

Hence, with the use of new technology systems, the decade of the 2010s registered an exponential increase in entrepreneurship that brought new and creative platforms and environments so that one could interact with the financial system again with trust and openness. Thus, this combination of Information Technology with Financial Services resulted in the beginning of the Fintech industry, an industry that many consider revolutionary to the financial and banking system.

Entrepreneurs, to materialize and launch their projects into the corporate world, usually need financial funding as well as mentoring from an investor (or a group of investors) that already has expertise in the institutional and corporate ladder. That's exactly where the Venture Capital industry comes in.

At most times, Venture Capital (VC) is the financial backbone of entrepreneurship. Entrepreneurs usually don't have the economic stability to support and invest all the funding that is needed for the idea (and start-up) to move forward. As such, founders lean toward the

VC industry to attract capital, mentorship, and networking (Hochberg, Ljungqvist & Lu, 2007). Venture Capitalists hope to successfully obtain financial returns when selling their shares at higher valuations, usually when the start-up is going through its Initial Public Offering (IPO) (D. J. Cumming & Schwienbacher, 2018).

This thesis aims to discover what are the drivers of VC investments in the Fintech ecosystem in Europe. I will study what were the investments that VCs made in Fintech startups during the four-year period between 2018 and 2021, a period during which this new ecosystem flourished due to high expectations of the market and the COVID-19 pandemic. I will also analyze possible factors that may impact that investment, whether that is the composition of the start-up or the type of VC institution (as we will see later, there are many types of VC firms). I will investigate the different investments that were made by local VCs and international VCs (if it was a cross-border investment or not) and observe if there is any difference between the two. Finally, I'll also separate the different areas of the fintech ecosystem and investigate what are the most attractive and demanded areas by VCs to allocate their investments.

Adding to the factors mentioned above, the statistical models will also account for macroeconomic factors such as the GDP amount and GDP growth of the country in which the start-up is based. With this correlation, some conclusions can be drawn if the investment made in the project is motivated by the economic health of the country.

The goal of this work is to understand a little bit more about Venture Capital and the impact that it has on the European Fintech ecosystem, as this is one of the most creative and disruptive sectors that financial markets have seen in their lifetime. Being a student (and an enthusiast) of Financial Markets (both public and private), I believe it is mandatory to understand this new disruptive Fintech technology that has the potential to change the financial and economic system. Our future as students and professionals may depend on it.

The thesis research will follow the next steps. Chapter 2 of the thesis will explore the literature related to the VC ecosystem and the Fintech industry. The literature review is mainly composed of scientific papers, as well as some reports made by online Private Equity (PE) intelligence platforms. Chapter 3 will uncover the methodology applied for this research, what are the statistical models applied and the variables used in those models. Chapter 4 of the research consists of the data obtained and applied to the models, as well as the use of summary statistics on the data. That way, it will be possible to get an overview of the current status of the Fintech system in Europe. Chapter 5 will be dedicated to the empirical results obtained through the statistical models. This chapter will be separated into two (Chapter 5.1 and Chapter 5.2), the first part being the study of a correlation matrix on the model's variables, while the second part is exclusively dedicated to the regression models that were applied. Finally, Chapter 6, the last chapter of the project, will focus on the final conclusions of the results obtained and what were the main points that were unveiled by the research.

2. Literature Review

In 1972, Bettinger defined fintech as "*an acronym which stands for financial technology, combining bank expertise with modern management science techniques and the computer*" (Bettinger, 1972). As already mentioned in the Chapter, Fintech is the conjunction of Information Technology (IT) and financial services (Milian et al., 2019), a combination that has long been made but has attracted new hype in the market due to its new approach to the Financial Services industry.

As IT has evolved and integrated new industries, it would be inevitable to also influence (and possibly disrupt) the financial sector. The first observations were the beginning of the Automated Teller Machine (ATM) networks during the 1970s, followed by electronic trading (the use of SWIFT messages) and the use of IT in internal operations (Bloomberg terminals are a perfect example), and finally the first use of online banking in the 1990s (Arner, Barberis, and Buckley, 2015).

However, the Financial Industry still had high issues with its operations and wasn't transparent enough for society, resulting in a few financial crises. With the occurrence of the 2008 financial crisis, society's trust in the financial services industry was completely broken, and banks were facing increasing supervision (Arner, Barberis, and Buckley, 2015). The technology industry could bring transparency to financial services operations as well as tighten up the relationship between the customer and the banks.

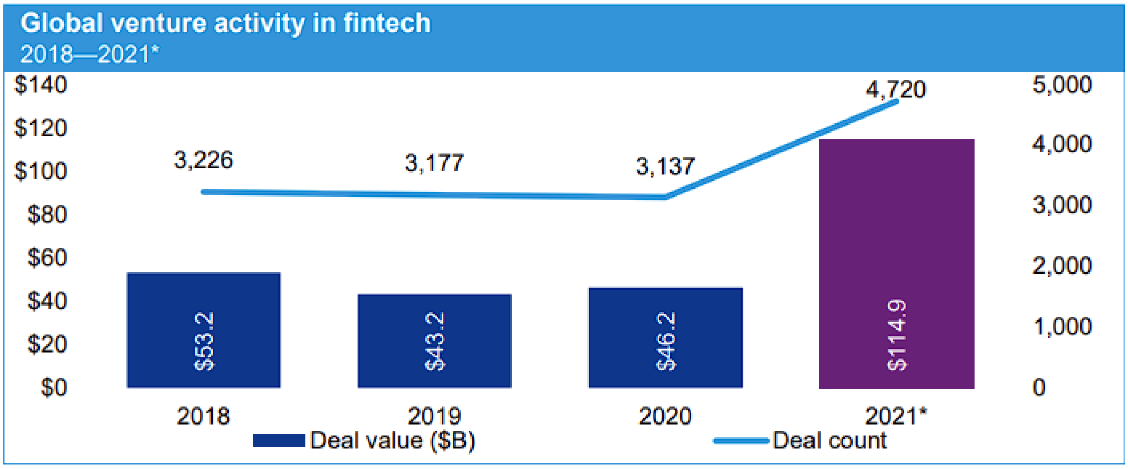
During this period, the traditional financial industry also could not supply the financial needs of small and medium enterprises (SMEs), as risk aversion was at an all-time high. Technology start-ups took that niche as an opportunity and became the providers of these SMEs (Fenwick, McCahery, and Vermeulen, 2017). Online lending platforms could offer new credit opportunities and improved efficiency and profitability, as they don't require much interest compared to banks and don't need any intermediaries for the exchanges between both parties. (OECD, 2015).

Fintech companies, filling the gap between the SMEs and financial funding, have created significant innovations in the markets, resulting in popularity growth among society. Traditional financial companies, observing this growth and realizing that their core activity was being faced with a new environment, built new entrepreneurial platforms to cooperate with start-ups over this technology (we can look at incubator programs as an example of that).

KPMG, one of the biggest global consulting companies, tracks the current status of the global Fintech sector constantly, dedicating a new report named "Pulse of Fintech" every quarter about the updated deal values and deal counts in Fintech. KPMG reports that the total fintech investment in the EMEA area grew to a new record of $77 billion in 2021 (KPMG, 2022), driven by the M&A activity, while the VC investment surpassed the $30 billion threshold, three times more than the investment account in 2020 ($9.9 billion). The report notes an increasing focus in the Insurtech area, while the Digital Banking industry remained the focus, with ventures achieving unexpected amounts of $900 million (N26) and $800 million (Revolut).

As shown in Figure 1 - Global Venture Activity in Fintech below, the deal values and the deal counts have greatly increased in 2021, thus showing the attraction that Fintech is obtaining. The deal counts, which were mainly constant in the 3200 units for the years from 2018 to 2020, have grown 50,46% into 4720 investments made in 2021. As the total deal value goes, 2021 accounted for an increase of $68,7 billion (more than doubled the total deal value of 2020). Hence, one can conclude that the average deal value, dividing the total deal value by the deal count, in 2021 was $24 million, a surplus of $10 million compared to 2020 (an increase of 65,29%).

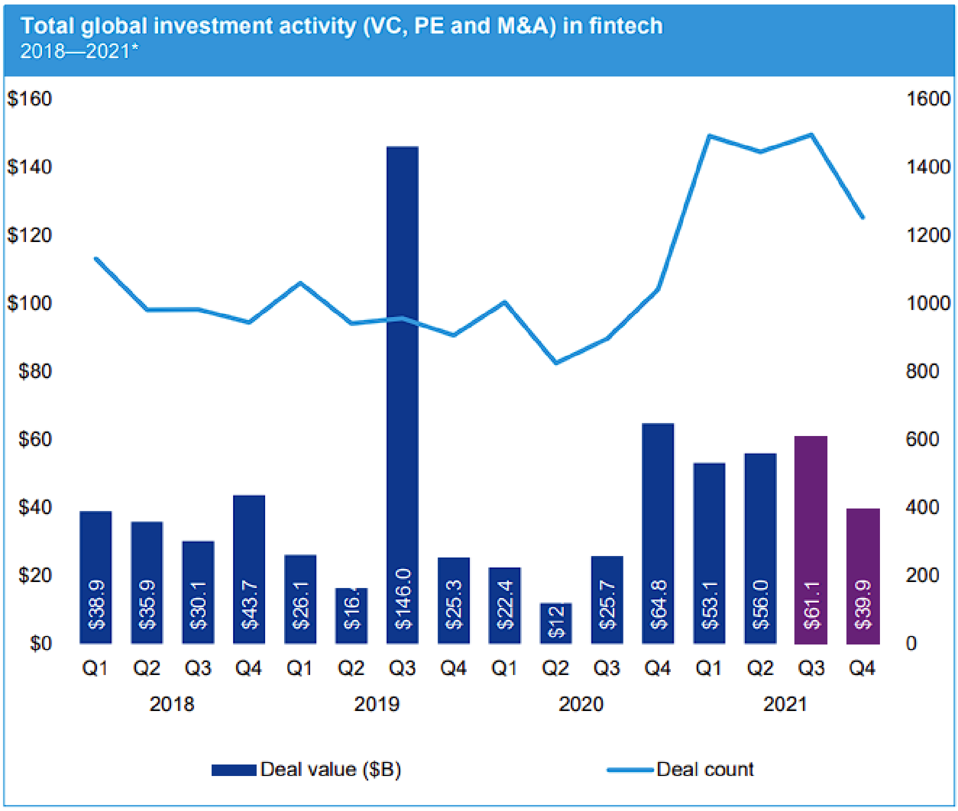
Figure 1: Global Venture Activity in Fintech



Source: Pulse of Fintech H2'21, KPMG International (data provided by Pitchbook), 2021

Looking at Figure 2 - Total Global Investment in Fintech, this is, aggregating all the Venture Capital investments with the PE and M&A sectors, during the same period, the same trend can be observed. The deal counts and deal values have greatly increased in 2021 (the growth actually started in Q4 of 2020). A special highlight must be given to Q3 of 2019, with a total deal value of $146 billion, the highest total deal value accounted for in these 4 years. The deal count suffered a slight decrease over the 2018-2020 period before starting to increase in Q4 of 2020 and then doubling in 2021, which also tracks the growth shown in Figure 1.

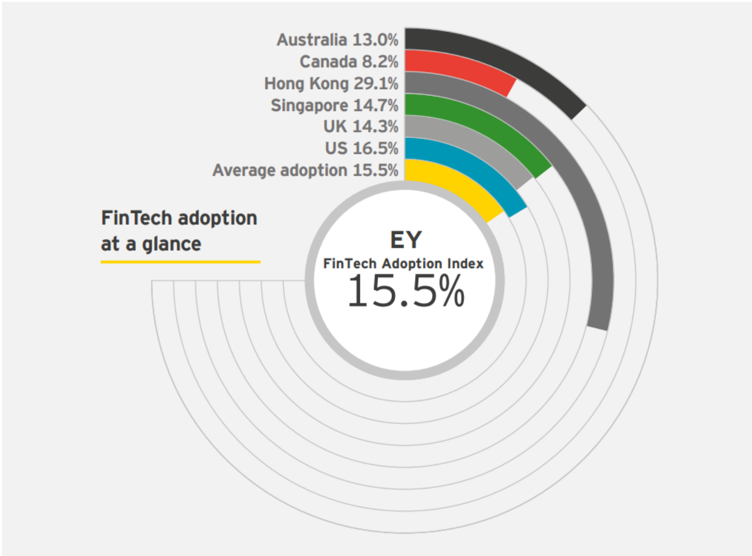
Figure 2: Total Global Investment Activity in Fintech



Source: Pulse of Fintech H2'21, KPMG International (data provided by Pitchbook), 2021

Fintech Services such as digital transfers and payments have allowed consumers to exchange money over themselves in a new and easier way than what traditional financial services such as banks provide. Hence, it should come as no surprise that the adoption rates for those platforms have been remarkably high, as users feel attracted to these platforms.

Figure 3: Fintech Adoption Rate



Source: The Journal of Financial Perspectives: Fintech, Volume 3 – Issue 3, EY 2015

Fintech (Arner, Barberis, and Buckley, 2015) doesn't just provide innovations in online banking (the authors actually use the term *Fintech 3.0*). As financial services become more networked, there is quicker access to digital payments; new platforms on equity crowdfunding, new marketplace lending programs, and chain financing innovations are also challenging traditional business models by reducing costs and risk, thus enhancing efficiency, and making SMEs more profitable. Banks have embraced Fintech technology to efficiently manage risk and improve compliance procedures (niche known as RegTech) by using Big Data analytics, Machine Learning (ML), Artificial Intelligence (AI), Internet of Things (IoT), and cloud computing (Fenwick et al., 2017; Hendershott et al., 2021).

Thakor (2019) identifies four main sectors of Fintech:

- Credit, deposits, and capital-raising services: P2P lending;
- Payments, clearing, and settlement services: cryptocurrencies;
- Investment management services: Robo-Advising.
- Insurance: Insurtech.

The author also defends that credit, deposits, and capital-raising services are much referred to as Peer-to-peer (P2P) lending. P2P lending is the loaning to individuals and enterprises through online services that directly correspond lenders with borrowers without the participation of a bank. The borrower submits an application for a loan. The P2P application analyzes the credit of the borrower and, consequently, provides a grade for the loan.

Furthermore, the lenders will propose loan amounts and interest rates to the borrower. The P2P platform does not offer capital to the loan, remaining independent of possible default by the borrower. It does, however, apply service fees to the borrower due to the service provided in the loan (Thakor, 2019).

The payments, clearing, and settlement services area is being heavily disrupted by cryptocurrencies, especially Bitcoin. Bitcoin is a technological code that operates as a digital currency. These virtual coins are housed on Blockchain, a ledger that substitutes a financial intermediary to verify the transactions made by consumers and relies on cryptography to provide security, ownership, and verification. Digital wallets are a type of payment technology that enables users to make transactions using their smartphones instead of physical wallets. Digital wallets can facilitate a variety of transactions, including peer-to-peer payments, purchasing tickets, and boarding passes.

According to his research, Anjan Thakor argues that Bitcoin is not an effective unit of account due to its extremely volatile market price and, at the same time, being traded at different market prices in different markets. This makes the asset vulnerable to arbitrage, which can lead to price discrepancies and instability. As a result, Bitcoin's effectiveness as a unit of account is highly questionable (Thakor, 2019).

Cryptocurrencies have created Initial Coin Offerings (ICO), a new mechanism to raise capital for start-ups to create a new project in the blockchain industry. The process is inspired by an IPO but exclusively applied to a cryptocurrency project. The project offers digital tokens or “coins” to investors in exchange for cryptocurrencies such as Bitcoin or Ethereum or traditional fiat currencies such as USD. These tokens are usually created on a blockchain platform and represent a share of the company's product, service, or project (Thakor, 2019).

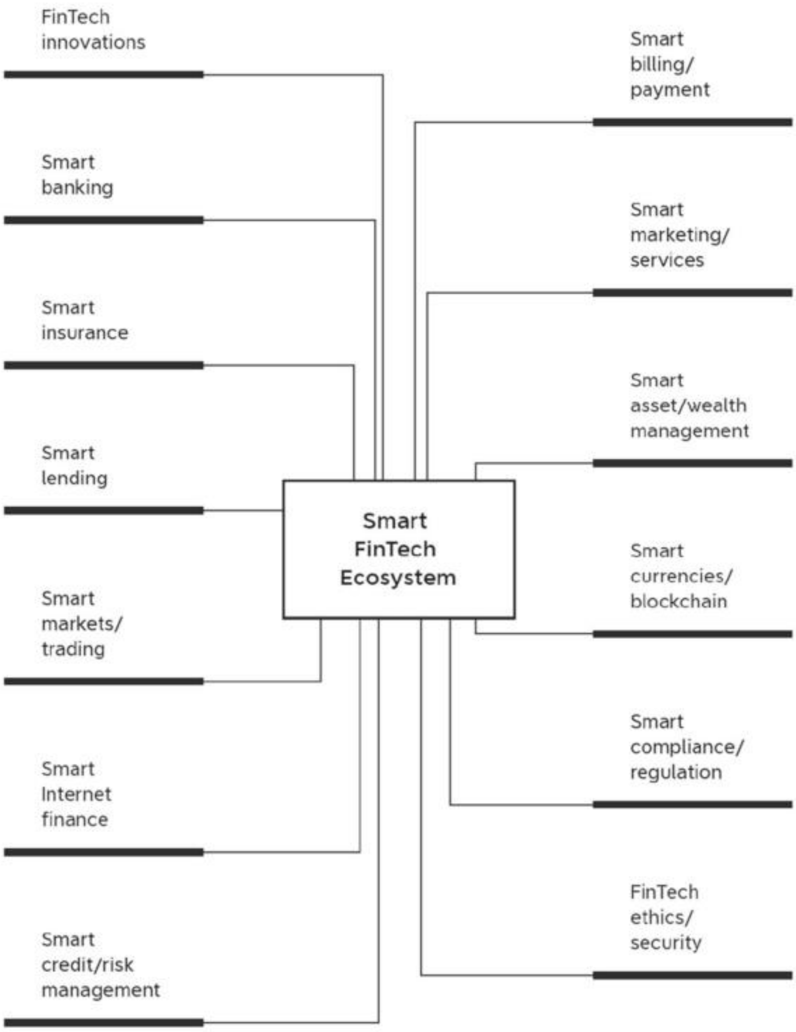
Investment management services are being affected by Robo-Advising, a digital platform that offers users algorithm-driven financial and investment planning and management. With Robo-advising, investors provide preferences about their financial goals, risk tolerance, and investment preferences. Based on this information, the Robo-advisor's algorithm generates a recommended investment portfolio that is tailored to the investor's needs (the investment strategy is heavily influenced by modern portfolio theory) (Thakor, 2019; D’Acunto et al., 2019).

Insurtech is the main technology driver that influences the Insurance industry, one of the main industries in the Financial Services ecosystem. Insurtech aggregates all the data that personal devices have and, with that information, can compute and risk more precisely and efficiently, and create new services for consumers. Insurtech also applies technological models like AI, Big Data, and Machine Learning, to offer transparent pricing models and personalized insurance products.

The fact is that we still don't know what this technology offers to its full potential. Relevant academic research on Fintech has been made to understand the impacts and solutions this technology can provide to individuals and enterprises. The Fintech "wave" has been sufficient for practitioners to compare it to the dot com bubble crisis of 1998-2000 (Cumming & Schwienbacher, 2018).

Data Science and Artificial Intelligence techniques (DSAI) are argued to be one of the biggest enablers of smart Fintech, the new era of Fintech. DSAI innovation enhances efficiency and intelligence on the companies' operations, personalized products and services to consumers, and cost-effectiveness and risk mitigation to the already existing financial systems (Cao, Yang, and Yu, 2021). The authors beautifully show, using the following graph, what are the main sectors that compose the smart fintech industry.

Figure 4: Smart Fintech Ecosystem



Source: Data Science and AI in Fintech: an overview – International Journal of Data Science and Analytics, 2021

The geographical localization of start-ups has also been extensively researched by academics and practitioners. Europe, in general, has embraced this ecosystem since the earlier years, with the UK being the epicenter due to the advanced financial market, accessible regulation, and Venture Capitalists' concentration. Germany, France, Benelux, and Ireland follow the list. Haddad and Hornuf (2016) reported that the more developed the capital market is, the higher the demand for fintech startups, as start-ups need capital to progress, and access to it needs to be easy (Haddad & Hornuf, 2016). VCs also benefit from the developed capital markets, as the exit options from the investment (in this case, the company) are more attractive (VCs tend to prefer exit through an IPO) (Gilson & Black, 1999).

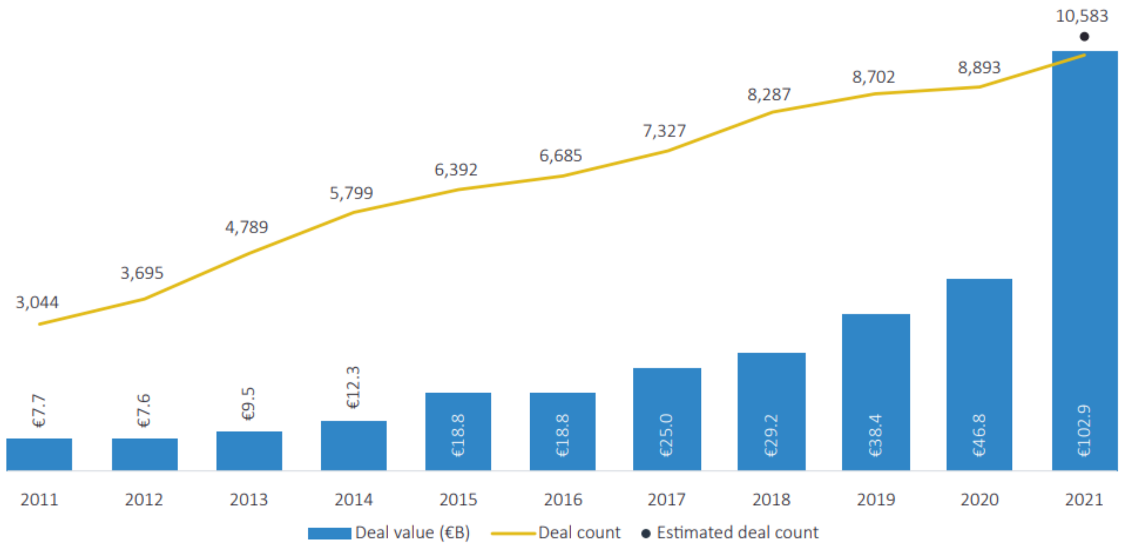
To gain a comprehensive understanding of Venture Capital, it is crucial to begin by defining its essence. Hence, Venture Capital refers to a subset of Private Equity focused on early-stage investments that extend capital to businesses for them to get started. In this context, it is worth noting the insightful perspective shared by Sullivan (2017), which offers a straightforward differentiation between Venture Capital and Private Equity: Private Equity primarily invests in established market firms, whereas Venture Capital predominantly supports startups right from their inception (Sullivan, 2017). Botazzi and Da Rin define the Venture Capital industry as an ecosystem of wealthy and/or institutional investors focused on unlisted creative ventures financing through equity or equity-like mechanisms (Bottazzi & Da Rin, 2002).

Zider (1998), in his research, expressed that the realm of Venture Capitalism lives among three main players: the entrepreneurs who conceive the start-ups and shape the business model, the investors who believe in these ideas and teams, and the possible intermediaries that make the connection between the previous two entities possible (Zider, 1998).

Zider (1998) also highlights that, even though VC plays a role in the funding of companies, VC's importance is diminished in the funding activity and basic innovation of early-stage start-ups. Only in more mature stages of the start-up (late-stage expansion phase), like the innovation life cycle to expand their businesses and create new products, do VCs really go through and become more important to entrepreneurs, as they can give new insights and facilitate new connections to other companies and founders (Zider, 1998).

During the 2010s decade, the late-stage VC’s activity expansion has been crucial to Fintech’s ecosystem expansion as the capital accounted for was €72 billion dollars, corresponding to 70% of the total VC deal value (Pitchbook, 2022). The Southern European ecosystem, even though it is behind compared to other regions in Europe, is catching up. Italy, Spain, and Portugal are attracting entrepreneurs and investors.

Figure 5: Annual VC Deal Activity



Source: European Venture Report 2021 Annual, Pitchbook, 19th January 2022

VCs usually secure their returns by providing funding in small private growth companies. These investments are usually done within a timeframe ranging from two to seven years, for the VC to earn financial returns through capital gains in exit transactions (Cumming, Fleming & Schwienbacher, 2005). Nahata (2008) found, due to his research, that start-ups that have creditable VC funding access public markets faster and have an increased probability of achieving a successful exit (Nahata, 2008).

Venture Capital organizations are usually structured as Limited Partnerships. The General Partners (GPs) control the operations and assume total responsibility, while also having to gather funding from other sources (other than the profits from the previous investments) in order to make their investments in the start-ups. In that sense, they approach Limited Partners (LPs), which are other main investors like institutional or corporate firms, universities, or even government programs, that provide the capital needed for GPs. It is important to highlight that LPs also bear no responsibility beyond that. By obtaining capital from limited partners, general partners can select new projects for investment (Bottazzi & Da Rin, 2002; Teker & Teker, 2016).

Jeng and Wells (2000) note, in their research, that IPOs are the most important determinant of Venture Capital investing. An IPO (Initial Public Offering) is a process that consists of a private company issuing shares of stock to the public capital market for the first time, hence raising funding from public investors. One can say that, when a company is performing an IPO, its ownership is going from private to public. The authors also conclude, in their research, that the possibility of the start-up performing an IPO in the future is a relevant factor in late-stage venture capital investment, but it's not significant in early-stage investment (Jeng & Wells, 2000).

There are two main types of Venture Capital investment, early-stage VC investment, and late-stage VC investment. The early-stage investment is composed of the Seed Capital, the Series A, and the Series B investment, while the late-stage investment is composed of Series C, Series D, and all other possible future Series investments. Seed Capital is an investment directed to promote product research and development (R&D), as well as assess its commercial potential. It is the first type of investment that a newborn startup secures. Following the Seed stage, the company is preparing to produce and sell its products and obtain a niche in the market. Even though the enterprise is starting to sell its new products, it uses more cash than what it produces. Hence, it should focus on obtaining Early-Stage investment from private Investors. Afterward, the startup if it remains successful, will enter the Late-Stage period. In this case, the company has defined its product and needs capital to enhance R&D and expand distribution and manufacturing. Thus, it should obtain this capital from Series C and Series D investments (and, if needed, more Series investments) from Late-Stage Investors.

The most known VC firm type is an independent VC. An independent VC is composed of the already mentioned GPs (the investors of the fund) and LPs (the source of capital to invest) (Sahlman, 1990). There are three more types of VC, the corporate VC (CVC), the bank-affiliated VC (BVC), and the governmental VC (GVC). These VCs are considered what one may call a captive VC, a venture vehicle to the holding company. The parent company of the corporate VC is a non-financial company, while BVCs are investment vehicles for financial intermediaries and GVCs to governmental agencies (Bertoni, Colombo & Quas, 2015).

The main IVCs in Europe are, for example, Balderton Capital, a leading early-stage VC fund focused on UK startups; Highland Europe, an IVC based in London that is also targeting UK and Swiss startups; and Global Founders Capital, an IVC located in Germany but invests in all European countries, not having a specific niche. An example of a GVC is the European Investment Fund (EIF), which also contributes capital not only to startups (acting as a GP) but can also provide funding to Venture Capital funds, exercising the ability of an LP (Bottazzi & Da Rin, 2002).

GPs are strongly sensitive to the founding team of the start-up as the operational capabilities of entrepreneurs matter greatly (Bernstein, Korteweg, and Laws, 2017). A team that engages with the start-up necessities while refusing tempting alternatives is greatly appreciated by GPs, as it shows investors that they truly believe in the potential of their project. Entrepreneurs can craft new businesses by adding an innovative component to an already-proven business model (Arend and Stern, 1999). Fintech is precisely that. New technology being added to an existing business model (Financial Services).

VCs consider possible agency and monitoring costs when evaluating how they should approach a specific project and provide capital to the start-up. They also periodically verify the condition of the project they invested in, as continuously surveying the start-up turns costly to the VC (Gompers, 1995). This author, in his academic study, argues that the number of financing rounds, the amount of a single investment, and the total investment obtained are significant variables of a possible investment opportunity.

Romain and La Potterie (2004) concluded that both interest rate and corporate income tax rate greatly affect the participation of Venture Capitalists. Countries that have higher market regulation strictness don’t benefit as much from higher GDP growth and, thus contract VC investment. These authors also prove that good technological opportunity indicators attract VCs. (Romain & La Potterie, 2004).

It is important to highlight that the Venture Capital industry doesn’t operate in the same way globally, this is, a Venture Capital organization based in China may approach new projects in a different way than a Venture Capital institution in South America. Focusing on the main markets (US VC industry and European Dutch VC industry), Brouwer and Hendrix (1998) discovered significant differences between the two, with respect to the share of early-stage ventures. According to their research, the European Venture Capital industry is more focused on LBOs (Leveraged Buyouts) and MBOs (Management Buyouts), instead of American VCs that target new companies (what one calls start-ups) (Brouwer & Hendrix, 1998).

Bertoni and Groh (2014) report that through VCs' networks of contacts and knowledge of their home countries, cross-border investments improve the exit options of the investors, boosting the efficiency of entrepreneurial finance. One can define cross-border investments as funding obtained by international investors (Bertoni & Groh, 2014). VCs' contacts with other clients and possible suppliers give them the freedom for companies to focus on their expertise instead of wasting time dealing with management (Bottazzi & Da Rin, 2002).

In the context of cross-border investments, cultural differences tend to exist. The Venture Capital field is no different. Nahata, Hazarika, and Tandon (2014) research proved that cultural discrepancies do affect Venture Capital investment's success. Significant cultural distance of the start-up compared to the VC surprisingly tends to enhance the probability of the funding's success, as VCs screen and choose more prudently potential investments to avoid getting more challenges managing the start-up than a local start-up investment would provide (Nahata, Hazarika, and Tandon, 2014).

Buzzacchi, Scellato, and Ughetto (2015) state that managerial incentives influence the general partners' decision to change the VC's fund risk profile, by including start-ups that aren't fully connected with the fund's original focus, resulting in what one may call a "style drift" (Buzzacchi, Scellato, and Ughetto, 2015). This style drift is the major concern of the limited partners, according to a survey done by Coller Capital, one of the biggest investors in the private equity market (Coller Capital, 2012).

3. Methodology

The previous chapter provided prior research and knowledge on the influence that Venture Capital has over entrepreneurship. It touched on the main characteristics of the Venture Capital industry, the different types of investments that are done in start-ups (series investments, for example), the composition of the firm, and the influence that it can provide to the founder and team, both financially and personally. The impact that a foreign VC could have on a local start-up was also shown. Additionally, the literature extensively approached the Fintech Industry, including the main core idea, the main areas of the Fintech sector as well as some specifics over each area, the attention that the ecosystem is attracting (due to the rise of the deal counts, and deal values over the last four years) and how it can impact society's daily life going forward.

In order to produce new research on the relationship between both sectors and what are the main drivers behind the investments that VCs do in the companies, the first step is to obtain a database where there is vast data on all the investments that are done on a specific local. In this case, the database will focus on the venture series investments that were made to this fairly new ecosystem in the Europe area, for the period of 2018-2021, a timeline of 4 years. Hence, I used Crunchbase's dataset to gather the main data needed (more information on the dataset is shown in the Data and Summary Statistics chapter).

On a first analysis of the VC-Fintech relation, a summary statistics analysis will be made on Crunchbase's database. That way, it will be possible to obtain an overview of the funding amounts, what are the main areas of the Fintech sector that attract investment, the composition of the team and what are the main financial and innovative centers of the European Fintech Ecosystem.

Next, it is important to understand how exactly the variables mentioned in the previous paragraph (and shown in the next chapter, Chapter 3 – Data and Summary Statistics) are correlated. Hence, a recommended statistical method to start is to apply a correlation matrix of all the important variables. Then, afterward, the statistical methods used for the research will be the Multiple Linear Regression Model (MLRM) in conjunction with the Ordinary Least Squares (OLS) method. Those models will be applied to various variables: firm's age, location, and area; stage of investment; VC's age, location, and focus, and amount of the investment.

Macroeconomic variables such as log GDP yearly value and GDP growth will also be used in the OLS in order to conclude if the investments in start-ups are also influenced by economic and financial macroeconomic variables.

The OLS is a model applied extensively in academic studies referenced in the existing literature. This model consists of applying a multiple linear regression model over some independent variables and a dependent one and estimating coefficients that describe the relationship between the variables. The assumptions underlying the MLRM impose that there should be no autocorrelation among the explanatory variables, hence the errors variables must be linearly independent. Nevertheless, when applying this model to time-series data, it frequently encounters violations of the mentioned assumption.

A factitious correlation between VC backing investment and enterprise growth may exist, which intensifies the odds of heterogeneity and multicollinearity. As Bertoni, Colombo, and Grilli (2011) reported, the growth of companies is closely related to the development of technology and the composition of the team (Bertoni, Colombo, and Grilli, 2011). These factors can change the potential to attract Venture Capital institutions. This situation may bias the coefficients of an OLS regression.

Then, to overcome the obstacle mentioned above, there are some statistical mechanisms that must be applied to the data. To overcome the error's first-order autocorrelation and the residuals' autocorrelation, the use of the Durbin-Watson (D-W) and the Breusch-Godfrey LM test, respectively, is recommended. In doing so, the independent and dependent variables will be correctively applied to the multivariate regression model.

The research will be done using the code language Python. Python is a popular programming language known for being user-friendly, easy, and simple to learn. It is highly used for data analysis and scientific computing but can also be used for web development and even artificial intelligence. Python supports modules and packages, which encourage program variety. The syntax is based on using indentation to indicate block structure instead of using other explicit delimiters. The platform used for the Python code is *Jupyter Notebook*.

The Python packages used for the research are the following:

- Numpy;
- Panda;
- Matplotlib;
- SKLearn;
- StatsModels;

4. Data and Summary Statistics

The data of the thesis is based on the Crunchbase database. To analyze VC's impact on the European Fintech sector, it is crucial to know what funding they are providing to start-ups. Hence, to answer this question, it is required to use a database that has at least most of the investments that were made in a specific location during a specific time. As the goal of the research is to analyze what is the relationship that Venture Capitalists have in the European Fintech Ecosystem, the location of the database investments must be in Europe. The timeline chosen for the database was between 2018 and ending in 2021, as it provides recent data to apply models.

In order to satisfy the goals referenced above, one of the chosen data sources was the Crunchbase database, the leading information provider of public and private companies and research solutions. This database has been used in various financial articles (Haddad and Hornuf, 2016). Crunchbase has registered most of the investments that were made globally, as well as who participated in that investment, the amount of the investment, and the type of funding.

This database used for the thesis' research carries the following data:

- Transaction name
- Organization's Variables (Name, Age, Nº Employees, Location, and Industry)
- Funding Variables (Stage, Type, Money Raised, and Date)
- Investors' Variables (Name and Location)
- Number of Investors (Age, Type)
- Number of Lead Investors
- Pre – Money Valuation
- Number of Funding Rounds
- Total Funding Amount

To apply the econometric methods to the Crunchbase dataset, in order to detect what were the relevant differentials of the VC's choice of investment, I created dummy variables over the following features:

- Class of Nº Employees (Dummy Variable)
- Type of Industry (Dummy Variable)
- Financial Center (Dummy Variable)
- Funding Stage (Dummy Variable)
- Investment made after covid (Dummy Variable)
- Type of VC (Dummy Variable)
- Angel Investor (Dummy Variable)
- Cross – Border Investment (Dummy Variable)

The macroeconomic variables GDP and Growth GDP (in %) were obtained from the World Bank Data database. The World Bank Data Portal is an international financial institution that collects and maintains a vast amount of data related to global development indicators, demographics, economics, health, and education and provides access to global economic and social statistics. The quantity of the IPOs by year and country was obtained from the Refinitiv Database. Refinitiv is a prominent force in the financial industry, offering an extensive array of databases and platforms catering to diverse requirements. Their expertise lies in providing financial market data, analytics, and trading solutions, making them a trusted source in the field.

Accounting for all the investments that were made during the period, the United Kingdom led the way in attracting investments, with 850 ventures, followed up by Germany with 187 investments and France with 129 fundings. Spain and Switzerland rounded the top 5 ranking with 120 and 78 ventures, respectively.

Table 1: Countries with the highest number of Ventures

Countries	Ventures (Number)
United Kingdon	850
Germany	187
France	129
Spain	120
Switzerland	78

Source: Crunchbase

Accounting for the areas of Fintech, the most ventured area was the Financial Services sector with 866 investments, followed by Online Banking with 394 financings. Blockchain technology accounted for 237 investments, Software-as-a-Service (SaaS) and Business Intelligence had 148 ventures, Financial Markets registered 78 fundings, and E-Commerce had 77 financial backings. The Insurtech and Crowdfunding sectors registered the lowest volume of ventures with 33 and 17 investments, respectively. As most start-ups approach two different areas simultaneously, a dummy variable was created to account for all the start-ups with 2 different areas. Hence, 1136 companies participate in two different industries, while 862 startups exclusively focus on a single sector.

Table 2: Fintech sectors with the highest number of Ventures

Fintech Sectors	Ventures (number)
Financial Services	866
Online Banking	394
Blockchain Marketplace	237
SaaS	148
Business Intelligence	148
Financial Markets	78
E-Commerce	77
Insurtech	33
Equity Crowdfunding	17

Source: Crunchbase

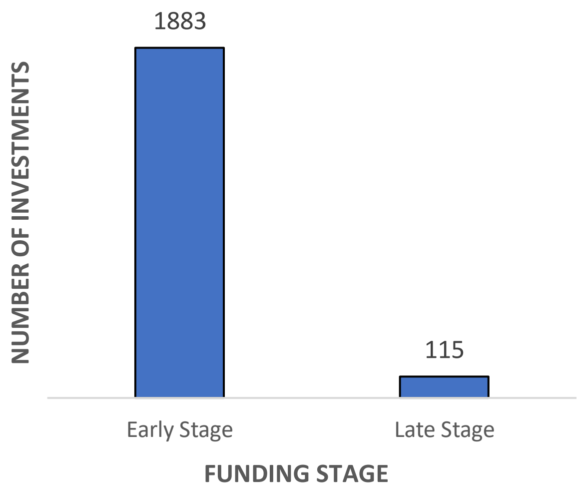
With regard to the stage of the funding, a significant majority of investments (94.2%) of the investments made by VCs were early-stage investments while just a small proportion (5.8%) of the financial backing was allocated to late-stage ventures. When considering the frequency of funding type, the most accounted venture type was the Seed stage with 824 investments, followed up by the Pre-Seed type with 524 ventures. This comes as no surprise, as the seed and pre-seed investments usually involve the smallest amounts. Given a fixed investment amount, a VC could choose to invest in numerous seed-stage startups or invest in a single late-stage funding. Interestingly, the Crunchbase database only accounted for 56 angel ventures during the 4-year period. The table below presents the number of ventures categorized by funding type.

Table 3: Funding Type with the highest number of Ventures

Funding Type	Ventures (number)
Seed	824
Pre-Seed	524
Series A	330
Series B	149
Series C	67
Angel Investor	56
Series D	25
Series E	13
Series G	6
Series F	3
Series H	1

Source: Crunchbase

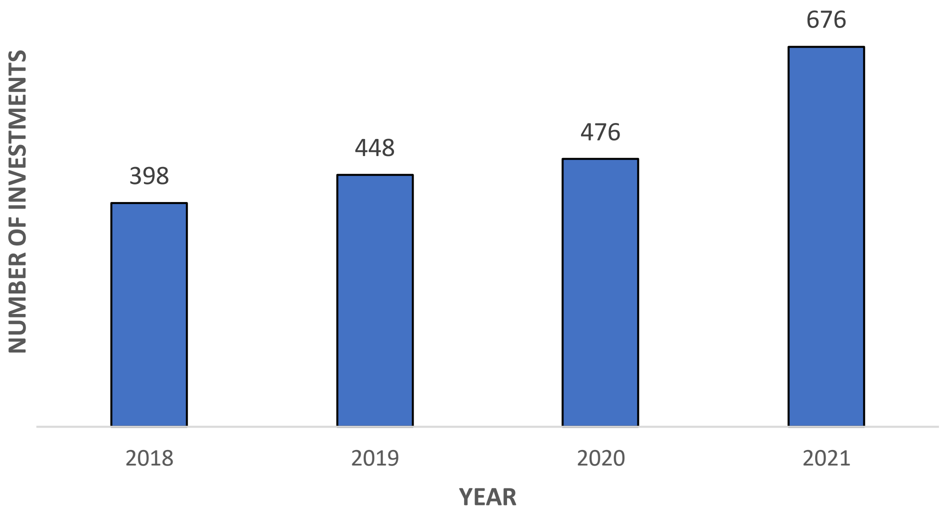
Graph 1: Funding Stage Investments



Source: Crunchbase

Accounting now for yearly investments, 2021 was the year that had the highest investment frequency of all with 676 ventures. 2020 followed with 476 VC backings, a difference of 28 financial rounds compared to 2019 which had 448 VC deals. Finally, 2018 was the lowest frequency year with 398 ventures.

Graph 2: Ventures made by Year.



Source: Crunchbase

Considering the type of Venture Capital firm that performed these investments, there is a clear predominance of Institutional Venture Capital (IVC). Accounting for a total of 1005 Venture Capital firms on the Crunchbase database for this period, 894 of those entities were IVC (a percentage of 88,96%). The Bank-Affiliate VCs type registered 31 investments, Corporate VCs made 27 ventures and Government VCs made 18 financial backings. Angel investors accounted for 35 ventures in the start-ups.

Table 4: Summary Statistics of the Money Raised by Start-ups

Money Raised (in USD)

	Total	2018	2019	2020	2021
Mean	14’608’945.25	6’074’006.54	9’962’175.81	9’626’175.88	26’222’046.62
Median	1’479’764	1’134’426	1’234’653	1’321’181	2’396’755.50
Min	1	1’000	1	1’000	1
Max	900’050’286	250’000’000	300’000’000	500’000’000	900’050’286
Standard Deviation	56’740’298.72	18’497’315.56	28’967’722.06	30’646’733.62	88’809’143.93
25% Percentile	400’000	251’952.50	362’187.50	388’496.25	548’895
75% Percentile	6’325’296	4’598’130	500’000	5’538’527.25	10’000’000

Source: Crunchbase

The summary statistics are provided in the following tables. **Table 4** - Summary Statistics of the Money Raised by Start-ups - is dedicated exclusively to the money raised by the European fintech start-ups with the Venture Capital firms. The average investment round during the 2018-2021 period was $14’608’945.25, with a growing tendency over the years. The average venture amount in 2018 was $6’074’006.54; in 2021, the average amount was $26’222’046.62. The median value also constantly grew over the sample years, as in 2018 the median value of the VC investments was $1’134’426, and in 2021 it was $2’369’744.50. In total, the median of the money raised by start-ups was $1’479’764.

The minimum investment accounted for the whole sample was just $1, while the biggest venture was $900’050’286, a venture that happened in 2021. The venture of just $1 was a seed round investment done in 2019 on the start-up *Bizao*, a start-up based in Paris that focuses on a combination of Financial Services with BI. The highest venture consisted of a Series E investment on N26, an internet banking start-up located in Germany that operates in various member states of the Euro Payments Area. The second biggest VC funding was $500’000’000 in 2020. The standard deviation of the sample is $56’740’298.72, with the 25% and 75% percentile being $400’000 and $6’325’296.

The growing tendency of the money raised by start-ups in investments follows the same tendency that the existing literature defines, as the demand and hope for these sectors are also growing exponentially. The financial market has also been very active in the sample years, which may also be a crucial factor for the VCs in allocating capital to these small enterprises. It is also important to highlight that it is highly difficult for these new companies to acquire highly capitalized ventures, as the difference between the maximum investment and the 75% percentile threshold is significantly large.

Table 5: Summary Statistics of the Total Funding Amount Obtained by Start-ups.

	Total Funding Amount (in USD)				
	Total	2018	2019	2020	2021
Mean	71’962’155.03	64’690’911.91	80’325’275.28	71’151’451.36	71’292’756.21
Median	5’874’908	5’026’882	6’967’760.50	5’195’795.50	5’548’812.50
Min	4’560	23’034	17’172	6’626	4’560
Max	2’154’045’440	2’154’045’440	1’830’000’000	183’000’000	183’000’000
Standard Deviation	226’385’168.22	218’286’768.31	242’849’423.56	223’714’603.02	221’401’177.37
25% Percentile	1’325’387	1’053’373	1’604’802.75	1’436’267.75	1’288’931.25
75% Percentile	26’350’724.50	23’154’555.75	30’890’847	24’663’858.25	26’899’511.25

Source: Crunchbase

The following **Table 5** - Summary Statistics of the Total Funding Amount Obtained by Start-ups - represents all the capital that start-ups have obtained since they started researching/operating. Our research aims to present a comprehensive summary of key statistical measures and insights derived from a carefully curated dataset of start-ups' funding amounts. By examining the distribution, central tendency, dispersion, and other critical metrics, we provide a clear and concise overview of the funding landscape within the start-up ecosystem.

The mean total funding amount remained relatively stable over the years, with an overall value of $71 million. The highest mean funding amount was in 2019 with a value of $80’325’275.28, while the lowest value was in the previous year, accounting for $64’690’911.91. The median funding amount, which represents the middle value, was consistently lower, ranging from 5 to 7 million dollars per year. The minimum funding amount ranged from four and a half thousand dollars to $23’034, a total difference of $18’474. The standard deviation, which measures the spread of the data, was relatively high, indicating a considerable degree of variability in the funding amounts.

In terms of percentiles, the 25th percentile funding amount ranged from around $1 million to $1.6 million, representing the lower end of the funding distribution. On the other side, this is, the upper end of the funding distribution, the 75th percentile funding amount ranged from around $23 million to $30 million. These percentiles provide insight into the spread of the data and give a sense of the range within which most funding amounts fell.

Table 6: Summary Statistics of the Countries with the highest number of Ventures

	Money Raised (in USD)						
	Mean	Median	Min	Max	Std Deviation	25% Percentile	75% Percentile
UK	18’005’413.37	1’867’846	1	800’000’000	58’285’349.60	453’347.50	5’493’549
France	12’529’942.20	3’199’948	1	162’532’666	26’071’990.75	1’230’242	9’300’000
Germany	35’322’623.20	4’864’957	8’377	900’050’286	110’665’793.60	1’106’272.50	21’668’813.00
Spain	2’807’432.68	710’553	20’000	73’182’869	7’629’437.99	259’744.25	2’220’060.25
Switzerland	5’268’650.21	1’712’002.50	72’107	38’000’000	7’800’848.35	693’318.50	5’235’860.75

Source: Crunchbase

As we explore the numbers and unveil the intriguing patterns underlying start-up funding, patterns that are relevant for this research, let's now dive into the insight that **Table 6** - Summary Statistics of the Countries with the highest quantity of Ventures – highlights, which consists of the money raised in USD by the country. In this case, I am accounting for the top 5 countries that had the most ventures, as shown previously in Table 1.

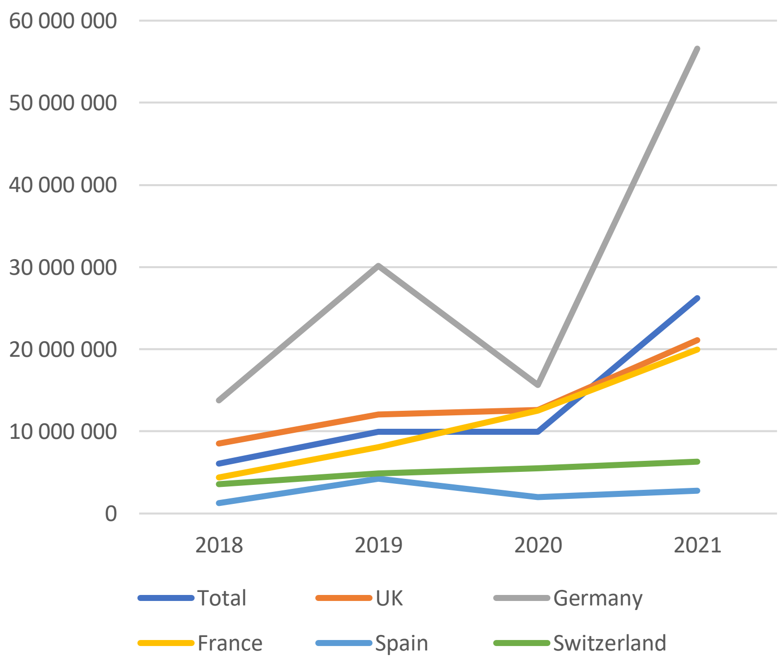
In the United Kingdom, the mean fundraising amount was $18'005'413.37, with a median of $1'967'846.00. The minimum amount raised captured by the Crunchbase dataset was just $1.00, while the maximum reached an impressive $800'000'000.00. The standard deviation of the ventures in the UK was $58'285'349.60, which indicates considerable volatility in the fundraising amounts. The 25th and 75th percentile accounted for $453'347.50 and $5'493'549.00, respectively. France, in comparison, exhibited a mean investment amount of $12'529'942.20, with a median of $3'199'948.00. The minimum amount raised was, again, $1.00, and the biggest amount accounted for reached $162'532'666.00. The standard deviation of $26'071'990.75, now suggests a decent level of variability. The 25th percentile was $1'230'242.00, and the 75th percentile was $9'300'000.00.

Germany got an unexpected spotlight recording a higher average fundraising venture capital of $35'322'623.20, with a median of $4'864'957.00, also higher than the other European countries. The minimum amount raised was $8'377.00, while the maximum amount stood at an impressive $900'050'286.00. The standard deviation of $110'665'793.60 indicates substantial variability in fundraising amounts. The 25th percentile was $1'106'272.50, and the 75th percentile was $21'668'813.00. Spain, in comparison, exhibited a relatively lower mean fundraising amount of $2'807'432.68, with a median of $710'553.00. The fundraising amounts ranged from a minimum of $20'000.00 to a maximum of $73'182'869.00. The standard deviation of $7'629'437.99 suggests a moderate level of variability. The 25th percentile was $259'744.25, and the 75th percentile was $2'220'060.25.

Switzerland displayed a mean fundraising amount of $5'268'650.21, with a median of $1'712'002.50. Switzerland's minimum amount was the highest of the top 5, with $72'107.00, while the maximum amount of the VC backing capital was $38'000'000. The standard deviation of the country was similar to Spain, with $7'800'848.35, a surplus of $171'410.36. The 25th and 75th percentile was $693'318.50 and $5'235'860.75, respectively.

As a resource to show the growth of the venture amounts in the mentioned countries by year, **Graph 3** below shows the average ventures by VCs for the sample years over the main countries that capture these investments. Considering the data that the graph highlights, it's clear to observe Germany's dominance over the other countries in venture amounts, as the mean venture amount is almost double that of its counterparties. This data is surprising, as the United Kingdom is the European country where most VC investments are made in Fintech and London is the city which many denominate as the "House of Fintech".

Graph 3: Average Venture by Year



Source: Crunchbase

The average growth of the venture amounts in Germany was of a significant 111%. The volatility of Germany is also clear to observe in the graph, as in 2019 the average amounts grew by 119%, but then diminished by 48% the next year (as the covid-19 pandemic hit), and then again grew exponentially by 261%. Even though the graph doesn't clearly demonstrate this growth, one should keep in mind that the Fintech innovation is one of the most wanted by Venture Capitalists.

The United Kingdom (65%) follows the same trend as the total European average ventures over the years (78%). The previous comes as no surprise as, again, most European ventures are made in this country. France also had a similar growth over the years, as the constant growth of the average venture by year was 66%.

Switzerland also has a constant growth over the years, but the growth itself was more subtle (average growth of 21%). Contrary to the already mentioned countries, Spain had its peak in the average venture investment in 2019, declining in 2020.

Table 7: Summary Statistics of the Fintech Sectors

	Total Funding Amount (in USD)						
	Mean	Median	Min	Max	Std	25%	75%
Financial Services	10’476’678.1	1’320’229.5	1	650’000’000	40’420’596.5	400’868.5	5’150’830.25
Online Banking	28’485’609.24	3’835’784.50	16’944	900’050’286	79’990’203.93	800’000	18’724’319.75
Blockchain Marketplace	13’707’786.22	904’679	4’560	9’000’000’000	72’878’084.50	216’585	3’040’000
Insurtech	9’890’084.64	4’064’096.00	120’000	63’000’000	13’407’510.37	914’452	13’526’857
Business Intelligence	4’641’009.01	847’729	7’000	2’000’000’000	17’334’461.14	220’239.25	3’525’000
Saas	6’855’637.53	2’082’251	2’368	1’000’000’000	12’978’148.01	482’231	6’960’512.25
Financial Markets	13’688’884.49	1’800’920.50	1’000	2’980’000’000	41’924’508.72	571’765	5’500’088.75
E-Commerce	32’252’338.55	1’144’100	24’831	793’770’157	107’032’946.37	354’146	15’705’473
Equity Crowdfunding	4’679’675.12	853’839	621	48’286’936	11’145’777.15	553’860	4’196’919

Source: Crunchbase

Additionally, more can be said about the current status of the Fintech ecosystem in Europe, as, for example, the investment capital that each area of this technology is attracting. Hence, in order to fill that need, **Table 7** and **Table 8** were created to present to the reader the summary statistics data on the amounts of venture raised (accounted in USD) for the various Fintech sectors.

For the Financial Services industry, the mean amount of investment raised was approximately $10’476’678.1, while the median value was $1’320’229.5. According to the CrunchBase dataset, the minimum amount raised was just $1.00, and the maximum amount was $650’000’000.00. The standard deviation, a statistical metric that measures the dispersion of values around the mean, was $40’420’596.5. The 25th percentile represents the value below which 25% of the data falls, and the metric was accounted at $400’868.5, while the 75th percentile, representing the value below which 75% of the data falls, accounted at $5’150’830.25.

Regarding the Online Banking industry, the average amount of capital raised by start-ups is significantly higher at approximately $28’485’609.24, with a median value of $3’835’784.50. The minimum amount raised is $16’944.00, while the maximum amount reaches $900’050’286.00. The standard deviation of the industry is $79’990’203.93, with the 25th percentile being $800’000.00, and the 75th percentile $18’724’319.75. The Blockchain Marketplace industry marked an investment mean and median of $13’707’786.22 and $904’679.00, respectively. The minimum amount raised held at $4’560.00, and the maximum $900’000’000.00. The standard deviation was $72’878’084.50, with the 25th percentile being $216’585.00, and the 75th percentile $3’040’000.00.

In the Insurtech industry, the mean amount raised in a venture was calculated at $9’890’084.64, and the median venture amount was $4’064’096.00. The minimum amount of VC funding was $120’000.00, while the maximum was $63’000’000.00. The standard deviation was $13’407’510.37. The 25th and the 75th percentile were $914’452.00 and $16’526’857.00, respectively. The Business Intelligence’s venture amounts had a mean of $4’541’009.01 and a median of $847’729.00, over the sample years. The minimum amount was raised to $7’000.00, and the maximum amount to $200’000’000.00. The standard deviation was $17’334’461.14. The 25th percentile registered an amount of $220’239.25, with the 75th percentile being $3’525’000.00.

For SaaS (Software as a Service), the data shows a mean and median investment amount of $6’855’637.53 and $2’082’251.00, while the minimum and maximum amount raised in this sector were $2’368.00 and $100’000’000.00, respectively. The standard deviation was $12’978’148.01, with the 25th percentile being $482’231.00, and the 75th percentile $6’960’512.25.

The Financial Markets industry had a mean amount raised of $13’688’884.49, with a median of $1’800’920.50. The minimum amount is $1’000.00, and the maximum is $298’000’000.00. The standard deviation is $41’924’508.72. The 25th percentile is $571’765.00, and the 75th percentile is $5’500’088.75.

In the E-Commerce industry, the mean amount raised was $32’252’338.55, and the median was raised at $1’144’100.00. The minimum amount accounted at $24’831.00, and the maximum at $793’770’157.00, with the standard deviation being $107’032’946.37. The 25th percentile was $354’146.00, and the 75th percentile $15’705’473.00. Finally, the Equity Crowdfunding industry had an average amount raised of $4’679’675.12 and a median of $853’839.00. The minimum amount was just $621.00, while the maximum was $48’286’936.00. The standard deviation was $11’145’777.15. The 25th percentile was noted at $553’860.00, and the 75th percentile peaked at $4’196’919.00.

Table 8: Average Ventures of the Fintech Sector by Year

	Average Money Raised (in USD)				
	Total	2018	2019	2020	2021
Financial Services	10’476’678.07	4’269’574.25	8’906’869.71	6’251’976.22	17’509’706.14
Online Banking	28’485’609.24	13’491’228.17	21’277’864.92	18’645’507.99	50’790’266.21
Blockchain Marketplace	13’707’786.22	2’045’333.67	3’248’742.79	5’102’463.98	30’204’182.86
Insurtech	9’890’084.64	2’806’429.20	10’992’383.09	9’150’614.43	12’737’013.20
SaaS	6’855’637.53	6’401’380.74	4’649’128.97	7’176’193.47	8’834’714.55
Financial Markets	13’688’884.49	12’867’399.69	6’716’173.43	6’690’775.29	23’920’435.52
E-Commerce	32’252’338.55	2’228’512.94	18’831’525.44	22’116’858.30	79’143’438.62
Equity Crowdfunding	4’679’675.12	3’347’517.33	7’444’895.29	-	2’486’151.14

Source: Crunchbase

In the Financial Services sector, the average venture amount provided by VCs was $10’476’678. This fundraising amount varied across the years, with $4’269’574.25 in 2018, $8’906’869.71 in 2019, $6’251’976.22 in 2020, and a significant increase to an average investment of $17’509’706.14, in 2021. The Online Banking ecosystem also witnessed substantial fundraising activities, accumulating a mean investment amount given to start-ups of $28,485,609.24. The amounts raised per year in this sector also show a progressive growth: $13’491’228.17 in 2018, $21’277’864.92 in 2019, $18’645’507.99 in 2020, and a peak of $50’790’266.21 in 2021.

The Blockchain Marketplace industry had, over the years 2018-2021, an average fundraising amount of $13’707’786.2. The VC backing amounts experienced fluctuations over the years, with $2’045’333.67 in 2018, constant growths in 2019 and 2020, and, again, a significant surge to $30’204’182.86 in 2021. Insurtech companies raised, on average, $9’890’084.64 per venture round. The fundraising amounts varied from $2’806’429.20, in 2018, and $12’737’013.20, in 2021.

The Business Intelligence industry accumulated, on average, a financing round of $4’541’009.01, while the industry SaaS (Software as a Service), in the same metric, raised a total average investment amount of $6’855’637.53. The Financial Markets industry gathered a total mean venture of $13’688’884.49, while E-commerce witnessed significant fundraising activities, accumulating a total average capital investment of $32’252’338.55. Finally, Equity Crowdfunding accumulated an average of $4’679’675.12, with the amounts raised of $3’345’717.33 in 2018, $7’444’895.29 in 2019, and $2’486’151.14 in 2021. Surprisingly, the CrunchBase dataset didn’t account for any Venture Capital investment in the Equity Crowdfunding sector in the year 2020.

5. Empirical Results

5.1 Correlation Matrix

Before starting with the Multivariate Analysis and the OLS model, I believe it is important to observe the correlation between some of the relevant variables in the Crunchbase dataset used in the Multivariate Analysis. Hence, a useful method to observe these correlations is to use a Correlation Matrix.

A Correlation Matrix is a statistical model applied to a dataset in order to evaluate the relationship between two or more variables. Consists of a table displaying a statistical method called Pearson's correlation (it can also apply Spearman's Correlation, but that won't be used in this project) coefficients between the variables that are applied to the model. The Correlation Matrix's main goal is to identify and highlight possible patterns between the variables.

The Correlation Matrix will consist of the Fintech area of the start-up (Online Banking or Insurtech, for example), the Money Raised in USD, the GDP amount of the country in which the start-up resides, the GDP growth (in percentage), and, finally, the IPO's that happened in the country in which the new company, again, resides.

The Correlation Matrix is shown in **Table 9** (shown in Appendix). By observing the Fintech areas that are most correlated with the Venture Raised by start-ups, Online Banking is the area that has the highest correlation, meaning that it's capturing the highest investments made by Venture Capitalists. Actually, Online Banking and E-Commerce are the only Fintech areas that have a positive correlation with the Money Raised variable, with correlation coefficients of 0.1212 and 0.0623, respectively, meaning that when one of the capital venture amounts increase, these two areas also tend to increase in value.

It is also interesting to see that, accounting for the variable GDP, most of the fintech areas have a negative correlation with the variable. Online Banking, Financial Services, and Financial Markets are the only areas with positive correlation coefficients (values of 0.0802, 0.0259, and 0.0044, respectively). Online Banking, thus, presents itself for now as the soundest area of the Fintech ecosystem, as it is the only with positively correlated with the round investment by VCs and the GDP amount.

However, Online Banking has a negative correlation with GDP Growth, meaning that the fintech area rises when the economy of the country or, accounting for this dataset when the economy of Europe itself suffers. E-Commerce and Financial Markets follow the same trend, as these are the only sectors of fintech with a negative correlation with GDP Growth.

Accounting now for the IPO variable, the negative correlation between the Blockchain Marketplace area is highlighted, with a coefficient of -0.0502. The value is surprising to an extent, as Blockchain and Cryptocurrencies are usually being hyped as the future of economy and technology, so it would be expected to see companies that invest and operate in the area to be highly demanded by investors and then, leading to great valuations and IPOs. However, one should not forget that, with the area being highly hyped nowadays, most entrepreneurs will try to create something new with this technology, even though the idea may not be good from the start. Hence, most of the start-ups created exclusively for Cryptocurrencies, don't create a product or a service of quality to consumers that is unique compared to other new companies, leading to failure.

The E-Commerce and the Equity Crowdfunding areas also have high negative correlations with the IPO variable. This, actually, should not come as a surprise, as these areas tend to find new ways for companies to obtain funding and revenue. If the stock market of a country is highly active, then it should be no problem for companies to obtain capital, and consumers will be eager to buy products/services of the start-up (assuming that an active stock market reflects a healthy economy for the country). Hence, the use of Equity Crowdfunding and E-Commerce should not be important for a company, as it obtains revenue easily. But, if a start-up or a project is located in a country in which the stock market is inflexible and investors tend to face problems in facing new projects, then these areas should be well-received for these small companies, as it gives optionality to obtain capital.

Online Banking, Financial Services, SaaS, and Business Intelligence have positive correlation coefficients with the IPO variable, showing that these products arise in countries in which the market is very active (United Kingdom and Germany, for example). Online Banking shows, once again, signs of being a sound and healthy investment in this new technology, with Financial Services following the trend.

5.2 Multivariate Analysis

As mentioned in the Methodology chapter, the OLS model is a statistical model created to make and explore multiple linear regressions between variables of a dataset. In this model, the regression is applied to a dependent variable and has, as the basis of the program, the values of the independent variables that the operator chooses to explore. In this sense, the user can observe if a change in the independent variables influences a possible change in the dependent one.

The multivariate equations used in the empirical results of the research will consist as follows:

$$Y = \beta_0 + \beta_1 FirmAge + \beta_2 FinancialCenter + \beta_3 Funding\ Rounds + \varepsilon i \quad (1)$$

$$Y = \beta_0 + \beta_1 LN(GDP) + \beta_2 GDPGrowth + \beta_3 LN(Total\ Funding\ Amount) + \beta_4 Funding\ Rounds + \beta_5 FirmAge + \beta_6 IPO + \varepsilon i \quad (2)$$

$$Y = \beta_0 + \beta_1 FundingStage + \beta_2 NumberInvestores + \beta_3 LeadInvestors + \beta_4 LN(GDP) + \beta_5 GDPGrowth + \beta_6 OnlineBanking + \beta_7 FS + \beta_8 SaaS + \beta_9 BM + \beta_{10} BI + \beta_{11} ECommerce + \beta_{12} Crowdfunding + \beta_{13} FM + \beta_{14} Insurtech + \varepsilon i \quad (3)$$

$$Y = \beta_0 + \beta_1 GP1 + \beta_2 GP11 + \beta_3 GP51 + \beta_4 GP101 + \beta_5 GP251 + \beta_6 GP501 + \beta_7 GP1001 + \beta_8 FinancialCenter + \beta_9 LN(Total\ Funding\ Amount) + \beta_{10} GDPGrowth + \beta_{11} FM + \beta_{12} IVC + \beta_{13} CVC + \beta_{14} BVC + \beta_{15} GVC + \varepsilon i \quad (4)$$

$$Y = \beta_0 + \beta_1 IVC + \beta_2 CVC + \beta_3 BVC + \beta_4 GVC + \beta_5 OnlineBanking + \beta_6 FS + \beta_7 SaaS + \beta_7 BM + \beta_8 BI + \beta_9 ECommerce + \beta_{10} Crowdfunding + \beta_{11} FM + \beta_{12} Insurtech + \beta_{13} FinancialCenter + \beta_{14} LN(Total\ Funding\ Amount) + \beta_{15} GDPGrowth + \varepsilon i \quad (5)$$

In order to observe the influence that Venture Capitalists have over the European fintech ecosystem, the first OLS regression model will consist of the dependent variable being the Money Raised in Ventures (accounting for USD) while the independent variables will be the Firm Age of the start-up, the Financial Center Dummy variable (considering whether the start-up is located in a financial center or not), and the number of funding rounds that the start-up has gathered until the moment of the last venture. **Graph 4** and **Table 10** below show the data obtained with the OLS model. The dependent variable Money Raised in Ventures (accounting for USD) will also be transformed into a logarithmic scale, as the true values of the investment are very volatile, and the use of statistical models would be unproductive.

According to the OLS model in **Table 10**, the constant coefficient of the dependent variable is 12.5187, indicating that the expected value of the dependent variable (LN (Money Raised Currency (in USD))) is 12.5187 when all independent variables are zero. All the tables are shown in the **Appendix**.

The firm age variable has a coefficient of 0.2074, meaning that for each unit increase in start-up age, the expected value of the dependent variable increases by 0.2074, assuming all other variables are constant. This result should not come as a surprise, as the longer the firm is operating, the higher the possibility that the product or service that is selling to the consumers is attractive to them. The second variable, the Financial Center dummy variable, had a coefficient of 1.0349. A positive coefficient shows, once again, that the relation between the two variables is positive, demonstrating that a start-up located in a financial center is highly attractive to Venture Capitalists. Since it is a dummy variable, the coefficient represents the average difference in the dependent variable between start-ups belonging to financial centers and those that do not, controlling for other variables.

Finally, the number of funding rounds variable also achieved a positive coefficient of 0.2014, indicating that for each additional funding round, the expected value of the dependent variable increases by 0.2014, assuming all other variables are constant. Then, a start-up obtaining venture fundraising increases the possibility of obtaining a new investment in the future.

The goodness-of-fit of the model is measured by the R-squared value, which, for this model, was 0.240. This indicates that the independent variables collectively only explained 24% of the variance in the dependent variable. It is important to note that the model's explanatory power is relatively low, as indicated by this metric. One could expect that the importance that the Firm age has on the investment amount (even though this variable is on a logarithmic scale) should alone be enough to get more than 24% percent, let alone the conjunction with the Financial center dummy and the number of funding rounds (a start-up that is located on London, for example, and is gathering a late-stage investment, should supposedly get more capital than a company that is located in Greece and is going for an early-stage investment). So, the R-squared being just 24% could become a letdown for a usual reader, however, it should also be recognized that these variables explain, at least, a quarter of the venture amounts raised.

Nevertheless, there are many more variables that define an investment made by a Venture Capital firm. Many of those variables couldn't even be transformed into data in this dataset (a crucial step in defining which start-up to invest in is the pitch, and the CrunchBase dataset doesn't have data over the pitches). Nevertheless, an R-squared of 24% shows that these variables, the start-up age, belonging to a financial center, and the number of funding rounds, could be significant factors in explaining the amount of money raised by start-ups in venture funding.

The F-statistic of the OLS model was 209.5, with a corresponding probability (Prob (F-statistic)) of 4.28e-118. This suggests that the overall regression model is statistically significant, indicating that the independent variables as a whole have a significant relationship with the dependent variable, which brings more power to the argument that these variables, although having a low goodness-to-fit, are still significant.

The model's diagnostics include the Omnibus test, which detects the presence of skewness and kurtosis in the residuals. The test yields a significant result (Prob (Omnibus) < 0.05), indicating non-normality in the residuals. The Durbin-Watson statistic is 1.790, which checks for autocorrelation in the residuals. A value between 1 and 2 suggests no significant autocorrelation.

As the goodness-of-fit of the previous model wasn't great, the use of new variables becomes important in order to obtain a cohesive and statistically attractive answer for the drivers of Venture Capital investment in European fintech start-ups. In this sense, I will apply macroeconomic variables such as the logarithmic scale of the GDP amount in the respective country and the year where the venture investment was made, as well as GDP growth. The IPO count is also included in the independent variables, as a country with high IPO processes could influence the investment made in the start-up. Finally, I will include the logarithmic scale of the Total Funding Amount obtained by the start-ups. The results are shown in Graph 5 and Table 10.

As the reader can observe in **Table 11**, the results of the OLS are significantly different from the ones obtained in **Table 10**. The multi-variate regression with macroeconomic variables as independent variables has a significantly greater goodness-of-fit to the dependent variable money raised than the start-ups' variables had. The R-squared of the model is now 69.4%, indicating that the independent variables collectively explain approximately 69.4% of the variance in the dependent variable. The constant coefficient of the regression is -0.4263, indicating that, when all the independent variables are zero, the expected venture is actually negative. This constant coefficient also has a p-value of 0.535, significantly greater than the 0.05 threshold, proving that it is statistically significant.

Previously the R-squared of the model (highlighted in **Table 10**) was just 24% and now, accounting for the values shown in **Table 11**, the R-squared is 69.4%, a major difference of 45.4%. The reader can, then, conclude that the impact that macroeconomic variables have on the amounts that VCs invested in must be, at least, greatly significant. Hence, these investments may not just be related to the specifics of the start-up, but how economically wealthy a country is.

Looking now at the coefficients of the independent variables, one can observe that the GDP on a logarithmic scale has a coefficient of 0.0870, which concludes that a one-unit increase in the logarithm of GDP is associated with an 8.7% increase in the expected value of the dependent variable, assuming all other independent variables in the OLS model are constant. The second independent variable of the model, GDP growth in percentage, has a great coefficient of 2.7357, which also suggests that a one-unit increase in GDP growth is associated with a significant increase in the expected value of the dependent variable of 2.7357. With this said, GDP Growth looks to be a major driver of VC investments in the fintech start-ups, which makes sense considering that a country with great GDP growth probably will have great economic prospects for the future, which brings trust and comfort to the start-ups that are based there.

The independent variable Total funding amount obtained by start-ups on a logarithmic scale had a coefficient of 0.8012, while the variable Number of funding rounds had a coefficient of 0.1407. Then, one can conclude that, regarding the third variable Total funding amount obtained by the start-up, a one-unit increase in the logarithm of the total funding amount is associated with a 0.8012 increase in the expected value of the dependent variable. The number of funding rounds variable now had a correlation coefficient of -0.1407, as an increase in the number of funding rounds of just one point is associated with a decrease in 0.1407 on the expected value of the dependent variable.

Finally, the variable Firm Age obtained, in the OLS model, a coefficient of 0.09, showing to the reader that a rise of one unit in firm age is associated with a 0.09 increase in the expected value of the dependent variable, assuming all other variables are constant. The last independent variable for the regression model, IPO count in the country of the start-up and the year that the venture happened, raised a coefficient of -0.0025. Although it is not statistically significant at the conventional 0.05 significance level (the P>|t| of the regression for this variable is 0.099), my interpretation of the results suggests that an increase in the IPO count may be associated with a slight decrease in the expected value of the dependent variable, controlling for all the other variables that are present in the model.

The F-statistic in the OLS model is 752.1, with a probability of 0.00. Hence, the overall regression model is statistically significant, indicating that the independent variables, as a whole, have a significant relationship with the dependent variable and, consequently, to the amount of the investment. The model's diagnostics include the Omnibus test, which detects non-normality in the residuals, with a significant result (Prob (Omnibus) greater than 0.05). The Durbin-Watson statistic in the model is 1.801, suggesting there is no significant autocorrelation in the residuals.

Overall, this updated OLS regression model suggests that variables such as GDP, GDP growth, total funding amount, number of funding rounds, firm age, and IPO count play a role in explaining the amount of money raised by start-ups in venture funding. However, the non-significant coefficient for the sixth variable suggests that further investigation may be necessary to determine its true impact on the dependent variable.

With the OLS model results shown above, the reader can conclude that macroeconomic factors such as the GDP amount and growth continue to have a greatly significant impact on the VC's decision to invest in a start-up. Hence, a healthy and growing economy makes venture capitalists more proponents of new and possibly riskier investments. These results are concise with the discoveries of Black and Gibson's (1999) research when they concluded that a healthy market motivates VCs to make ventures, assuming that a wealthy country has an active stock market (using the UK and Germany for inspiration).

In fact, the macroeconomic variables, according to the OLS model, are more important than the characteristics of the company itself, as the R-squared now was 69,4% and, of the previous model, was just 24%. A surprising discovery was the non-statistically significant impact of the IPOs that existed in the country of the start-up. One could assume that if a country has a lot of companies going through an IPO process, then the market economy of the country and the potential for another company to follow that same going public procedure would influence VC's investments, as Venture Capitalists' major return possibility is, itself, an IPO. However, one has to keep in mind that the capital markets in which the IPOs tend to exist are fairly different markets than the ones that are dominated by VC investments. VC investments are more dominant in early-stage markets, while the IPOs are predominant in later-stage markets, in which the firm is, supposedly, stable and captures enough earnings to go public. Either way, this absence of the IPO factor could be interesting to see more future research on this matter.

However, more research needs to be done on what are the drivers of VC ventures in start-ups. The fact that a growing market is significant on the VC side of the investment doesn't explain why some start-ups are chosen and others aren't so lucky. It's not possible to analyze every single characteristic of the investment (as mentioned before but still highly important during this research, the start-up's pitch is an essential step to the VC deal process and due diligence and, unfortunately, there is no data on these factors on the dataset). But, if one applies the area of the start-up as an independent variable, then maybe it'll be possible to observe if there is a preference for a specific area.

With this being said, a new OLS model was made, with the dependent variable still being the money raised in a venture on a logarithmic scale, and the independent variable being the logarithmic scale of the GDP amount as well as the GDP growth (macroeconomic variables), the number of investors and lead investors, the funding stage of the venture (whether it was early-stage of late-stage), and the area of fintech sector (mentioned in the data and summary chapter). The results can be seen below and in **Table 12** and the graph of the Ordinary Least Squares sample is shown in **Graph 6** (both shown in the Appendix). The choice to use categorical variables, like the type of the area in which the start-up belongs to, as dummy variables was inspired by the work of Bertoni and Groh (2014), in which the authors also used the same method in their research in order to create statistical models that could analyze the impact of cross-border investments.

The R-squared value of the OLS model is 0.443, showcasing that the relation of the independent variables with the dependent variable LN (Money raised currency (in USD)) explains approximately 44.3%. The adjusted R-squared value adjusts the R-squared value for the number of predictors in the model. For this case, the adjusted R-squared value in this model is 0.438, which is not a significant difference. However, the R-Squared is significantly inferior to the R-Squared obtained in the last OLS model (shown in **Table 11**), which is surprising considering that the macroeconomic variables are still present as independent variables and the remaining variables may be considered more relevant to the start-up, as we are now considering the fintech area that the start-up operates at as well as the funding stage of the start-up, two relevant factors to the start-up. The number of investors and lead investors is also important to the amount in the venture raised, as a venture in a company that is performed by various investment firms should be higher than a venture that is performed by just a single VC. Thus, these results should be taken with a grain of salt.

Adding to the robustness of the Ordinary Least Squares model, the F-statistic test result is 87.80, an attractive result that proves the overall significance of the regression model. The associated probability (Prob (F-statistic)) is also very small (8.32e-172) compared to the normal threshold, indicating that the model as a whole is statistically significant.

Now, before checking for the behavior of each variable in the OLS model, one can observe that the estimated coefficient for the constant term, the intercept of the regression line, is 5.2856, with a standard error of 1.626.

In this model, there were four independent variables that had p-values greater than 0.05, indicating they weren't statistically significant. Those were the cases of GDP Growth and the fintech areas of Blockchain Marketplace, Business Intelligence, and Equity Crowdfunding. These results are surprising and interesting to an extent, especially the GDP growth and the Blockchain Marketplace. The GDP growth was already observed in the last OLS model and its relation to the venture variable was statistically significant, so the change of importance from one model to another is unexpected. The Blockchain marketplace being not statistically significant is also interesting, as this sector is specialized in what many assume is the future of finance and money itself. Then, technology being the future of what is crucial in society's currency of value should have, at least, a great upside. Venture Capitalists are attracted to projects that have great upside in order to obtain huge returns, so the relationship between these investors and cryptocurrency start-ups should be positive and statistically significant.

The Durbin-Watson (DW) result in the OLS model is 2.003, showing there may exist autocorrelation between the sample's variables, even though that autocorrelation would be low since the recommended threshold of the DW test is 2. The Jarque-Bera (JB) test result is 12.528. The Prob (Omnibus) of the model is 0.004, which indicates the non-normality of the variables.

The Crunchbase dataset provides information about the composition of the start-up team and its size that can be fruitful to explore. A firm that has only 10 collaborators will probably be in its seed stage and won't gather massive amounts of funding, while another company that has over 300 professionals on its books will be in a growth stage and then, will capture a greater amount of investment. Hence, the use of the group size could be a great source of influence for the investment amount. Additionally, its correlation with the type of VC fund could be interesting to explore, as IVC could be searching for early stage ventures (the upside is greater and have more tolerance to risk), while a GVC could be searching for later-stage ventures (the risk is not as high). So, I believe that both factors should be used as explanatory variables at the same time on the OLS. Hence, the next model (shown in **Table 13**), will consist of the group size (dummy variables), type of VC fund (dummy variables), Financial center (dummy variable), GDP growth, and LN (Total Funding amount) as explanatory variables, while the LN (Venture amount) will be dependent variables.

As the reader can observe in **Table 13**, the results of the OLS are significantly different from the ones obtained in **Table 12**. The multi-variate regression with macroeconomic variables as independent variables as well as the type of Venture Capital firm has a greater goodness-of-fit. The R-squared of the model is now 67.4%, indicating that the independent variables collectively explain approximately 67.4% of the variance in the dependent variable. The constant coefficient of the regression is 3.4171, indicating that, when all the independent variables are zero, the expected venture is actually positive. This coefficient also has a p-value of 0 significantly greater than the 0.05 threshold. These indicators greatly differ from the OLS models that were previously applied to the macroeconomic data (shown in **Table 10** and **Table 11** of this research).

Taking a first look at the investors side, and observing the coefficients of the independent regression variables, one can observe that all types of Venture Capital, but the BVC funds have p-values greater than the 0.05 threshold, concluding that they aren't statistically significant. This data becomes interesting, as the reader could expect that the type of VC could change the purpose of the start-ups in what they invest. It is important to remember that the database has a great bias toward IVC companies, as most of the CVC, GVC, and BVC investments aren't on the database. If one can gather all the remaining data and apply it to the Crunchbase dataset, the empirical results probably would greatly differ (however, that process is way beyond the scope of this research).

Now switching the focus back to the start-ups' side, the reader can see that the explanatory variables of small group size, dedicated to the segment of 1 collaborator to 50 collaborators and the 50 professionals to 100, have p-values of 0.12 and 0.121, respectively. Hence, these factors aren't statistically significant to the venture amount captured by the seed firm. However, once the firm goes through the 50 professionals threshold, the p-value decreases to a percentage of 4.6% and keeps decreasing as long as the company continues to gather collaborators for its project. This correlation is interesting, as one can observe the continuous change of a variable (group size) that initially isn't statistically significant, but then changes and becomes significant to the dependent variable. Hence, we can conclude that this factor is relevant to the venture fund and the choice of investment, as it has a direct correlation with the amount of the investment.

Considering the type of start-up, the p-values of these variables are all lower than the p-value threshold of 0.05, with the exception of the E-Commerce and Equity Crowdfunding start-ups, which obtained statistical values of 0.055 and 0.179. Mainly all these variables' coefficients are also positive, with the Equity Crowdfunding being the only start-up type with a negative coefficient of -0.3672, hence a one-unit increase in the logarithmic scale of the money obtained in the investment is related to a 36.72% decrease in the Equity Crowdfunding type. As this area has the purpose of being an alternate way of obtaining capital from the more traditional choices, this negative correlation becomes reasonable.

The independent variable Total funding amount obtained by start-ups on a logarithmic scale had a coefficient of 0.6808. In this sense, one can conclude that, regarding the third variable Total funding amount obtained by the start-us, a one-unit increase in the logarithm of the total funding amount is associated with a 0.6808 increase in the expected value of the dependent variable, assuming all other variables are constant. The last independent variable of this OLS model, GDP Growth, obtained the best statistical results from all the other variables, as the coefficient of the correlation with the dependent variable is 2.3507, while the P>|t| is exactly 0.

The F-statistic result in the OLS model is 315.6, with a probability of 0.00. Hence, the overall regression model is statistically significant, indicating that the independent variables, as a whole, have a significant relationship with the dependent variable. The model's diagnostics include the Omnibus test, which detects non-normality in the residuals, with a significant result (Prob(Omnibus) greater than 0.05). The Durbin-Watson statistic in the model is 1.856, concluding there is no significant autocorrelation in the residuals.

Overall, this updated OLS regression model suggests that variables such as IVC, CVC, BVC, GVC, the composition of the start-up (firm size), the logarithmic scale of the funding amount obtained by the start-up, and the GDP Growth also play a role in explaining the amount of money raised by start-ups in venture funding.

Even though some conclusions can be drawn with the knowledge that the OLS regressions provide, I still believe that there should be studied the correlation between the type of venture funds and the area of focus of the start-up. The IVC sector could be more inclined to the Online Banking sector while the CVC sector could express its interest on the Blockchain technology, for example. Hence, the next OLS model will include as explanatory variables the different types of VC funds and the area of start-up (both as dummy variables), the logarithmic scale of the total investment obtained by the start-up and the GDP growth (in %). The results are shown in **Table 14** and **Graph 8**.

By looking at the results obtained from the regression, the first indicator that we notice is that the R-Squared diminished 0.004 percentual points, which is not significant, to a value of 0.67. Either way, it hasn't increased, which was the optimal target of regression. The F-statistic of the model accounts for 268, with a probability of 0.00. The D-W of the model is1.846. Taking a focus on the correlation between the variables, the constant coefficient of the model is 2.4370, thus the expected value of the investment is positive if all the independent variables account for 0.

There were 5 explanatory variables that had p-values greater than the 0.05 limit. The IVC, CVC, and GVC kept surpassing the threshold, confirming that they aren't statistically significant for the model, while the BVC is the only VC fund type that had a p-value lower than the threshold. The E-commerce and the Equity Crowdfunding sectors also obtained P>|t| greater than 0.05, showing that these industries also aren't statistically significant to the amount of the investment. All the other explanatory variables were statistically significant. The variables that had the highest coefficients were, once again, the GDP Growth and the Total funding amount obtained by the start-up (in an LN scale), with the addition of the Insurtech area and the BVC fund type.

Aggregating all the data shown in the last pages, the reader can conclude that, in fact, there are drivers that influence the investment of the VCs in the Fintech sector. The main drivers of these investments aren't exclusively related to the start-up itself, even though they eventually have a share over the investment decision made by General Partners. If the start-up variables didn't play a role, then there would be no difference in investing in a well-managed start-up or a badly managed one. In this sense, the investment criteria that entrepreneurs go through in order to obtain capital would be completely unnecessary.

However, based on the multivariate regression models that were applied in this research and the results obtained from it, the macroeconomic variables such as the GDP amount by country and GDP growth are the main relevant factors of VC investments. These results make economic sense, since if these investment firms didn't have good macroeconomic prospects for the future, they would be more rigorous with their investment choice, which probably would lead to a decrease in the number of investments made and, consequently, the decrease of the total investment made by VCs in fintech start-ups (actually, this approach would impact all start-ups, not just fintech). Additionally, General Partners would also be more pressured to obtain financial returns and give them to the Limited Partners, as these would also pressure GP in order to not lose money (or time). This pressure could lead to more pressure applied to the entrepreneurs and corrupt the start-up growth. The relationship between the two companies could become unhealthy and that can lead to an unsuccessful investment.

The use of a Generalized linear model could be interesting for this research (a mentioned in the Methodology chapter), since it is a regression model that is more flexible than the traditional regression model, as it can be fueled by variables that aren't continuous.

Overall, the provided Generalized Linear Model Regression, using the Poisson distribution as the basis and log link function, that can be shown on **Table 15**, seems to have a poor statistical significance for the included independent variables in explaining the count data of money raised in a Venture, on a logarithmic scale. The pseudo-R-squared value (0.1549) provides a measure of how well the model fits the data, which, in this case, is not the greatest result, as a higher value indicates a better fit, and in this case, it suggests that the model explains about 15.49% of the variation in the dependent variable. However, it is important to highlight that, since this is a pseudo-R-squared, it may not be directly comparable to R-squared values from ordinary linear regression models.

The estimated coefficients for the independent variables are provided in **Table 15**. For example, the coefficient for GDP value in a log scale and the GDP growth (in percentage) is 0.0647 and 0.4960, respectively. One can observe, again, that GDP growth is greatly correlated with the funding obtained by a start-up in a series of venture investments. The log scale of the Total Funding Amount's variable coefficient is 0.0578, while the Number of Funding Round's variable coefficient is -0.0107, and the Firm Age and IPO coefficients are 0.0062 and -0.0020, respectively. One could also expect, as shown previously, that the Funding Round's coefficient would be positive, as a start-up that had many venture investments would expect that the next funding obtained by a VC would be greater than the previous ones. However, this is not always the case. The start-up may not need a high investment by VCs (the financial need may not be great, or the start-up doesn't want to give up a high stake of the ownership).

The standard errors of the variables are relatively small, while the z-scores of the LN (GDP) and LN (Total Funding Amount) are highly significant to the dependent variable. The z-scores are calculated by dividing the coefficients by their corresponding standard errors and they help assess the statistical significance of the coefficients. It is also important to highlight that the Number of Funding Rounds and IPO variables has a negative z-score, with respective values of -4.126 and -6.995.

Based on the provided results, all six independent variables are statistically significant since their p-values are well below 0.05. Therefore, we can conclude that these variables have a significant impact on the dependent variable (LN (Raised Currency (in USD))) in this Poisson GLM.

The reader, before reading the research, could assume that the variables IPO count and Total funding rounds were considerable variables that would influence the regression model, as these factors could change the nature of the venture obtained to the start-up. In fact, according to the regression models, these variables are statistically significant, hence they are statistically relevant to the Ordinary Least Squares models that were applied. However, the use (or absence) of the variables made no difference in the R-squared measure of the regression models, thus concluding that their statistical influence is actually limited. I believe it's important to highlight that these variables could show their influence on another data set, future research that focuses on these two aspects could be interesting.

6. Conclusion

The purpose of this paper was to identify, quantify, and compare the influence that the Venture Capital industry had over the European Fintech ecosystem. More specifically, to know what the main drivers of the VC investment over the European fintech start-ups were. As this is a new segment of the financial market, it should be interesting to conclude how this niche has been growing over the last few years.

There were many limitations to the construction of this research. The data was difficult to gather, as the dataset belongs to Crunchbase, a paid premium platform that extensively limited its use for the users that were using it on a free trial plan. Additionally, it was interesting for this research to use market indexes dedicated to the European sectors of Fintech and Venture Capital, but these indexes were relatively new in Europe (for more information, the reader can check the market indexes created by Refinitiv) and the use of statistical models wouldn't be generated effectively, due to the low number of observations. Hence, the results could be biased, due to autocorrelation, and that would damage the research that was already done with the Crunchbase database.

Over the literature review chapter, there were a significant number of references that indicated precisely the impact that Fintech had and could have for the next years, among all the mentioned areas that can bring innovation to the already established, and essential, traditional financial models. In the same chapter, there were also some references to the business model of the traditional Venture Capital industry, as well as the different types of Venture Capitalism.

Following the summary statistics of the dataset, the reader can observe that the evolution of this segment is following the same trend that the literature review mentions, as the demand of this market is growing considerably, taking into account the number of investments that have almost duplicated in 2021 compared to 2018, a remarkable evolution of just a four-year gap. The mean amount of the investment has also grown exponentially, as the average investment in 2018 was 6 million dollars, and in 2021, was now 26 million dollars.

The empirical results that the Ordinary Least Squares regression models obtained, when applied to the variables of the Crunchbase dataset, are satisfying to a degree. The reader can conclude, due to the growth of the R-Squares measure, that the macroeconomic variables are considered to be the main drivers of VC investment. However, when computing and analyzing the results obtained, I was expecting that the start-up's variables, such as the number of funding rounds that the start-up had gathered or its location (financial center or not) would have a greater impact than the one captured through the regression models. Again, this doesn't mean that these factors don't have any impact on the investment decision by VCs, it's just that their significance, which was obtained in the OLS regression models, is not statistically attractive compared to the results expected.

The empirical results also concluded that the firm size of the start-up, this is, the number of collaborators that are on the project, also has an impact on the venture amount invested by the VC company. Not only that factor can be a driver of the investment, but some of the areas in which the start-up inserts itself into are statistically significant to the investment. I was expecting the type of VC fund to also be relevant, but, according to the regression models, those variables aren't statistically significant.

This "problem" actually creates, or justifies, the need to research more about this market. There are still many possible factors that can be considered and, consequently, are known to be significant to the investment decision by the Venture Capital group. One can use a database that captures the investments that were made in a different region and get significantly different results, or one could use a dataset that focuses on different types of Venture Capital firms and broadcasts a higher correlation between the two industries. One could even use the same dataset but apply more years to the study (historical years or even future), and the correlations obtained through the variables could be completely different. More research is highly recommended. Maybe the wider yearly gap will show the true (or effective) impacts that the start-ups' variables have over the investment criteria.

The research has shed light on a crucial correlation between the state of a country's economy and the performance of its venture capital market, especially in the context of the dynamic Fintech sector. Hence, taking a major focus on Portugal, one takeaway that I would like to point out is that if we want to empower ourselves with all the new technology and knowledge that this ecosystem can provide, it is imperative that we prioritize and enhance our macroeconomic conditions. Achieving a favorable threshold in these factors will not only beckon new market opportunities but also attract a wealth of fresh talent, which can completely change our landscape socially, economically, and politically.

It's a vision of progress, innovation, and economic vitality. But to make this vision a reality, we must act decisively and collaboratively. The rewards can be immeasurable.

References

Arend, R. J., & Stern, L. N. (1999). EMERGENCE OF ENTREPRENEURS FOLLOWING EXOGENOUS TECHNOLOGICAL CHANGE. In Strategic Management Journal Strat. Mgmt. J (Vol. 20).

Arner, D., Barberis, J., Buckley, R., Law, U., Arner, D. W., & Buckley, R. P. (2015). THE EVOLUTION OF FINTECH: A NEW POST-CRISIS PARADIGM?

Bernstein, S., Korteweg, A., & Laws, K. (2017). Attracting Early-Stage Investors: Evidence from a Randomized Field Experiment. Journal of Finance, 72(2), 509–538.

Bertoni, F., Colombo, M. G., & Grilli, L. (2011). Venture capital financing and the growth of high-tech start-ups: Disentangling treatment from selection effects. Research Policy, 40(7), 1028–1043.

Bertoni, F., Colombo, M. G., & Quas, A. (2015). The patterns of venture capital investment in Europe. Small Business Economics, 45(3), 543–560.

Bertoni, F., & Groh, A. P. (2014). Cross-Border Investments and Venture Capital Exits in Europe. Corporate Governance: An International Review, 22(2), 84–99.

Bettinger, A. (1972). FINTECH: A Series of 40 Time Shared Models Used at Manufacturers Hanover Trust. In Source: Interfaces (Vol. 2, Issue 4).

Bottazzi, L., & Da Rin, M. (2002). Venture capital in Europe and the financing of innovative companies. Economic Policy.

Brouwer M, & Hendrix B. (1998). Two Worlds of Venture Capital: What Happened to U.S. and Dutch Early Stage Investment? Small Business Economics, 10(333–348).

Buzzacchi, L., Scellato, G., & Ughetto, E. (2015). Investment stage drifts and venture capital managerial incentives. Journal of Corporate Finance, 33, 118–128.

Cao, L., Yang, Q., & Yu, P. S. (2021). Data science and AI in FinTech: an overview. In International Journal of Data Science and Analytics (Vol. 12, Issue 2, pp. 81–99). Springer Science and Business Media Deutschland GmbH.

Coller Capital. (2012). A UNIQUE PERSPECTIVE ON THE ISSUES AND OPPORTUNITIES FACING INVESTORS IN PRIVATE EQUITY WORLDWIDE Global Private Equity Barometer.

Cumming, D., Fleming, G., & Schwienbacher, A. (2005). Liquidity Risk and Venture Capital Finance. In Financial Management.

Cumming, D. J., & Schwienbacher, A. (2018a). Fintech Venture Capital.

D'Acunto, F., Prabhala, N., & Rossi, A. G. (2019). The Promises and Pitfalls of Robo-Advising. In Review of Financial Studies (Vol. 32, Issue 5, pp. 1983–2020). Oxford University Press.

Fenwick, M., Mccahery, J. A., & Vermeulen, E. P. M. (2017). Fintech and the Financing of Entrepreneurs: From Crowdfunding to Marketplace Lending. https://ssrn.com/abstract=2967891

Gilson, R. J., & Black, B. S. (1999). Does Venture Capital Require an Active Stock Market? In JOURNAL OF APPLIED CORPORATE FINANCE (Vol. 11, Issue 4). https://scholarship.law.columbia.edu/faculty_scholarship

Gompers, P. A. (1995). American Finance Association Optimal Investment, Monitoring, and the Staging of Venture Capital. In Source: The Journal of Finance (Vol. 50, Issue 5).

Haddad, C., & Hornuf, L. (2016a). The Emergence of the Global Fintech Market: Economic and Technological Determinants. https://ssrn.com/abstract=2830124

Hendershott, T., Zhang, X., Leon Zhao, J., & Zheng, Z. (2021). Fintech as a game changer: Overview of research frontiers. Information Systems Research, 32(1), 1–17.

Hochberg, Y. V, Ljungqvist, A., & Lu, Y. (2007). Whom You Know Matters: Venture Capital Networks and Investment Performance. In THE JOURNAL OF FINANCE •: Vol. LXII (Issue 1).

Jeng, L. A., & Wells, P. C. (2000). The determinants of venture capital funding: evidence across countries. In Journal of Corporate Finance (Vol. 6).

KPMG. (2022). Pulse of Fintech H2’21.

Milian, E. Z., Spinola, M. de M., & Carvalho, M. M. de. (2019). Fintechs: A literature review and research agenda. Electronic Commerce Research and Applications, 34.

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

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

OECD. (2015). New Approaches to SME and Entrepreneurship Financing: Broadening the Range of Instruments 2.

Pitchbook. (2022). European Venture Report.

Romain, A., & Van Pottelsberghe, B. (2004). The determinants of venture capital: A Panel Data Analysis of 16 OECD Countries. https://www.researchgate.net/publication/24131038

Sahlman, W. A. (1990). The structure and governance of venture-capital organizations. In Journal of Financial Economics (Vol. 27).

Sullivan, T. D. (2017). What do venture capital and private equity firms do? Some current and historical examples. Journal of Business and Finance Librarianship, 22(3–4), 182–189.

Teker, S., & Teker, D. (2016). Venture Capital and Business Angels: Turkish Case. Procedia - Social and Behavioral Sciences, 235, 630–637. https://doi.org/10.1016/j.sbspro.2016.11.041

Thakor, A. V. (2019a). FINTECH AND BANKING: WHAT DO WE KNOW? https://ssrn.com/abstract=3429223

Zider B. (1998). How Venture Capital Works. Harvard Business Review.

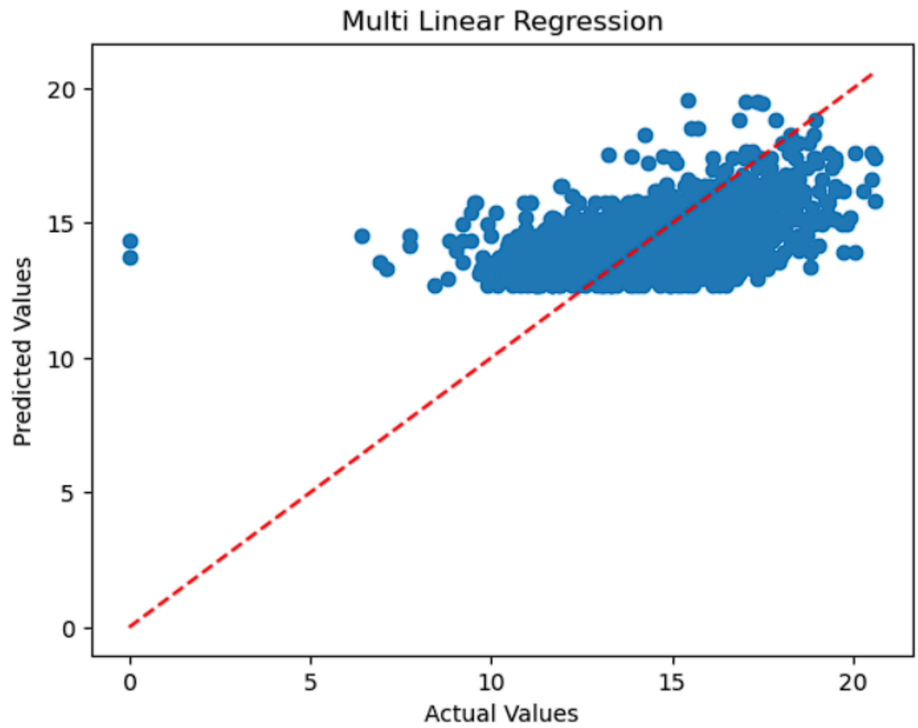
Appendix

Table 9: Correlation Matrix

	Online Banking	Financial Services	Saas	Blockchain Marketplace	Business Intelligence	E-Commerce	Equity Crowdfunding	Insurtech	Financial Markets	Money Raised Currency (in USD)	GDP	GDP Growth	IPO
Online Banking	1.0000	-0.4335	-0.1402	-0.1818	-0.1402	-0.0992	-0.0459	-0.0642	-0.0999	0.1212	0.0802	-0.0632	0.0495
Financial Services	-0.4335	1.0000	-0.2474	-0.3209	-0.2474	-0.1751	-0.0810	-0.1133	-0.1763	-0.0637	0.0259	0.0129	0.0207
Saas	-0.1402	-0.2474	1.0000	-0.1038	-0.0800	-0.0566	-0.0262	-0.0367	-0.0570	-0.0386	-0.0068	0.0162	0.0139
Blockchain Marketplace	-0.1818	-0.3209	-0.1038	1.0000	-0.1038	-0.0734	-0.0340	-0.0475	-0.0739	-0.0058	-0.0593	0.0355	-0.0502
Business Intelligence	-0.1402	-0.2474	-0.0800	-0.1038	1.0000	-0.0566	-0.0262	-0.0367	-0.0570	-0.0502	-0.0309	0.0036	0.0199
E-Commerce	-0.0992	-0.1751	-0.0566	-0.0734	-0.0566	1.0000	-0.0185	-0.0259	-0.0404	0.0623	-0.0726	-0.0122	-0.0636
Equity Crowdfunding	-0.0459	-0.0810	-0.0262	-0.0340	-0.0262	-0.0185	1.0000	-0.0120	-0.0187	-0.0162	-0.0257	0.0383	-0.0613
Insurtech	-0.0642	-0.1133	-0.0367	-0.0475	-0.0367	-0.0259	-0.0120	1.0000	-0.0261	-0.0108	-0.0027	0.0212	-0.0231
Financial Markets	-0.0999	-0.1763	-0.0570	-0.0739	-0.0570	-0.0404	-0.0187	-0.0261	1.0000	-0.0033	0.0044	-0.0087	-0.0093
Money Raised Currency (in USD)	0.1212	-0.0637	-0.0386	-0.0058	-0.0502	0.0623	-0.0162	-0.0108	-0.0033	1.0000	0.1418	0.0572	0.0656
GDP	0.0802	0.0259	-0.0068	-0.0593	-0.0309	-0.0726	-0.0257	-0.0027	0.0044	0.1418	1.0000	-0.0869	0.5666
GDP Growth	-0.0632	0.0129	0.0162	0.0355	0.0036	-0.0122	0.0383	0.0212	-0.0087	0.0572	-0.0869	1.0000	0.1654
IPO	0.0495	0.0207	0.0139	-0.0502	0.0199	-0.0636	-0.0613	-0.0231	-0.0093	0.0656	0.5666	0.1654	1.0000

Source: Crunchbase

Graph 4: OLS Regression Model



Source: Crunchbase

Table 10: OLS Regression Results Table

OLS Regression Results

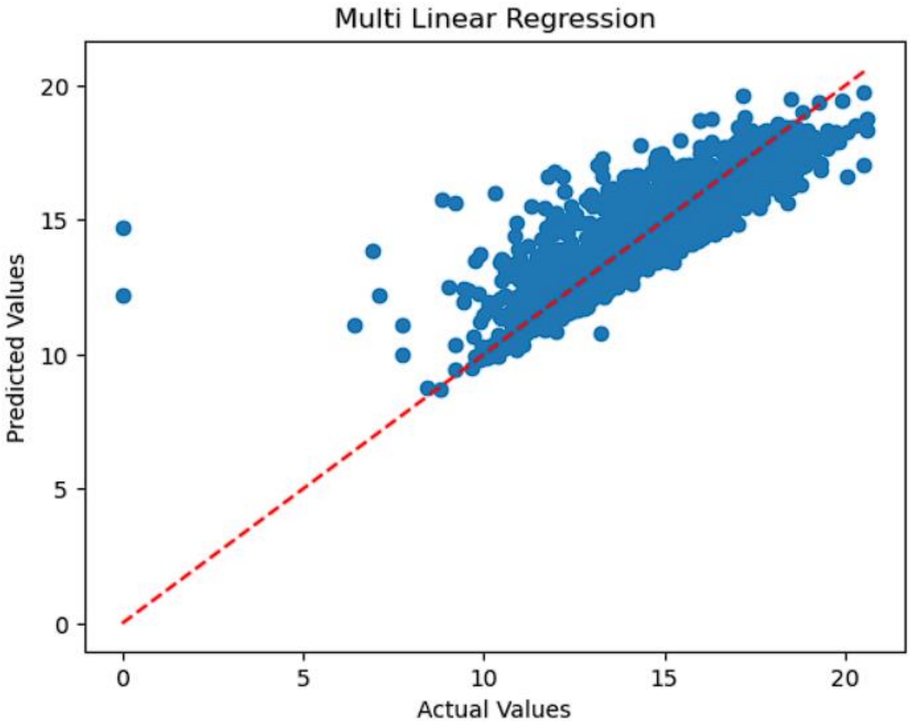
Dep. Variable:	LN (Money Raised Currency (in USD))	R-squared:	0.240
Model:	OLS	Adj. R-squared:	0.238
Method:	Least Squares	F-statistic:	209.5
Date:	Mon, 05 Jun 2023	Prob (F-statistic):	4.28e-118
Time:	14:44:54	Log-Likelihood:	-4081.3
No. Observations:	1998	AIC:	8171.
Df Residuals:	1994	BIC:	8193.
Df Model:	3		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	12.5187	0.083	150.761	0.000	12.356	12.682
x1	0.2074	0.015	13.428	0.000	0.177	0.238
x2	1.0349	0.115	9.033	0.000	0.810	1.260
x3	0.2014	0.016	12.561	0.000	0.170	0.233

Omnibus:	249.490	Durbin-Watson:	1.790
Prob(Omnibus):	0.000	Jarque-Bera (JB):	1006.411
Skew:	-0.554	Prob(JB):	2.89e-219
Kurtosis:	6.296	Cond. No.	18.6

Source: Crunchbase

Graph 5: OLS Regression Model



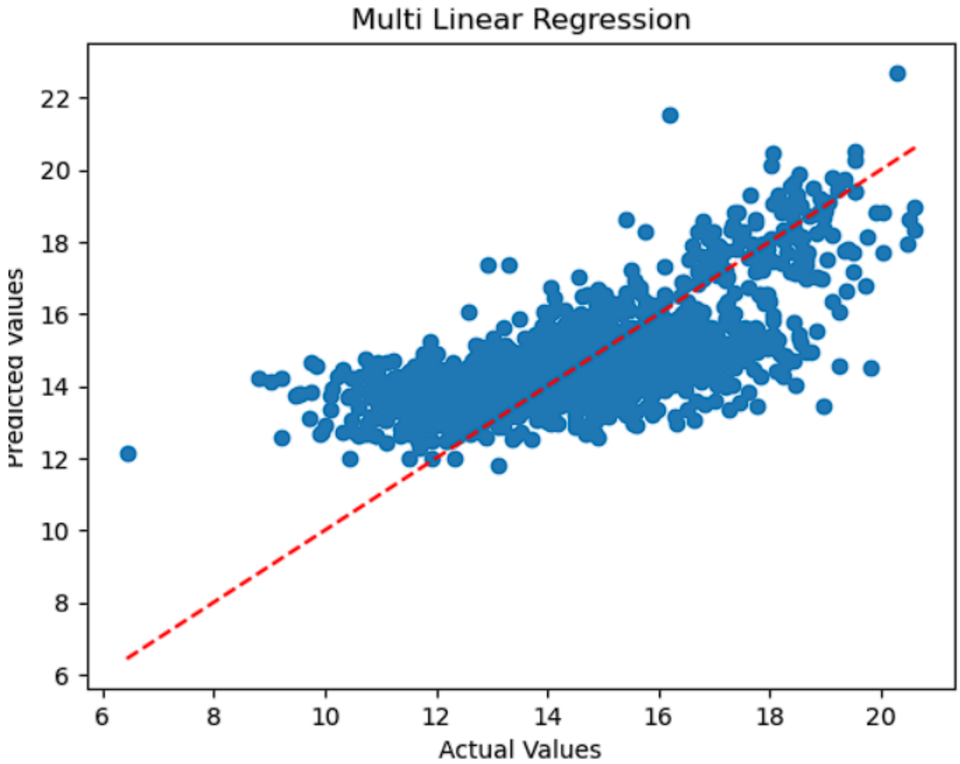
Source: Crunchbase

Table 11: OLS Regression Results Table

```
                                  OLS Regression Results
==============================================================================================
Dep. Variable:     LN (Money Raised Currency (in USD))   R-squared:                      0.694
Model:                                            OLS   Adj. R-squared:                 0.693
Method:                                 Least Squares   F-statistic:                    752.1
Date:                                Mon, 05 Jun 2023   Prob (F-statistic):              0.00
Time:                                        14:44:54   Log-Likelihood:               -3172.5
No. Observations:                                1998   AIC:                            6359.
Df Residuals:                                    1991   BIC:                            6398.
Df Model:                                           6
Covariance Type:                            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -0.4263      0.686     -0.621      0.535      -1.773       0.920
x1             0.0870      0.026      3.357      0.001       0.036       0.138
x2             2.7357      0.489      5.598      0.000       1.777       3.694
x3             0.8012      0.015     53.586      0.000       0.772       0.831
x4            -0.1407      0.012    -11.797      0.000      -0.164      -0.117
x5             0.0900      0.010      8.912      0.000       0.070       0.110
x6            -0.0025      0.002     -1.649      0.099      -0.005       0.000
==============================================================================
Omnibus:                     1277.422   Durbin-Watson:                   1.801
Prob(Omnibus):                  0.000   Jarque-Bera (JB):            34240.971
Skew:                          -2.560   Prob(JB):                         0.00
Kurtosis:                      22.623   Cond. No.                     1.17e+03
==============================================================================
```

Source: Crunchbase

Graph 6: OLS Regression Model



Source: Crunchbase

Table 12: OLS Regression Results Table

OLS Regression Results

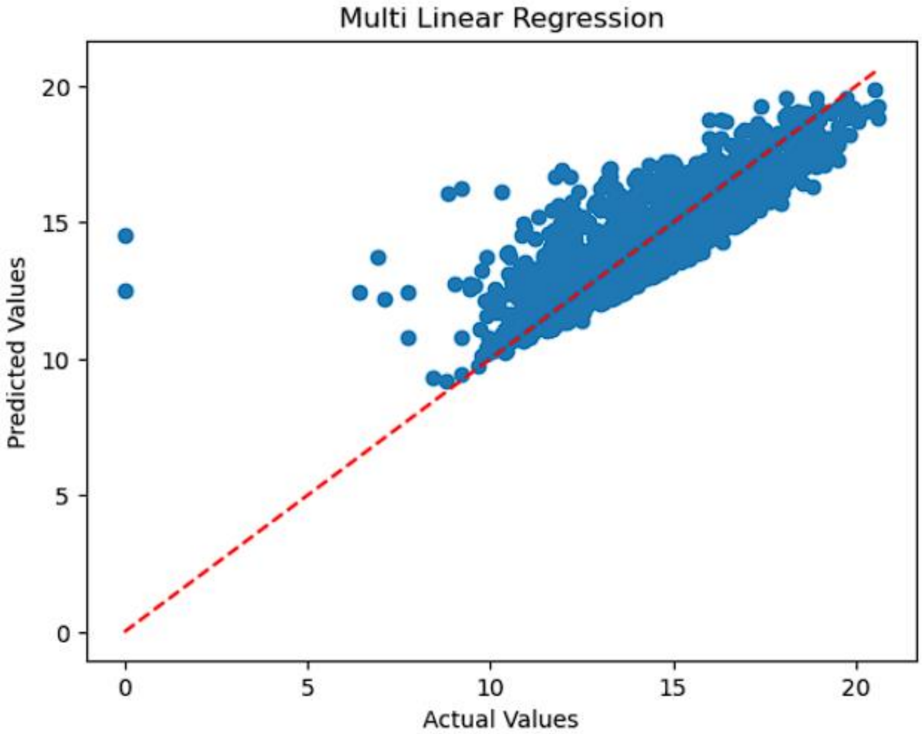
Dep. Variable:	LN (Money Raised Currency (in USD))	R-squared:	0.444
Model:	OLS	Adj. R-squared:	0.439
Method:	Least Squares	F-statistic:	88.11
Date:	Sat, 10 Jun 2023	Prob (F-statistic):	2.76e-172
Time:	13:56:53	Log-Likelihood:	-2700.7
No. Observations:	1450	AIC:	5429.
Df Residuals:	1436	BIC:	5503.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	4.2847	0.821	5.219	0.000	2.674	5.895
x1	2.7537	0.164	16.795	0.000	2.432	3.075
x2	0.2311	0.016	14.565	0.000	0.200	0.262
x3	0.4696	0.057	8.289	0.000	0.358	0.581
x4	0.3050	0.033	9.286	0.000	0.241	0.369
x5	1.1993	0.749	1.600	0.110	-0.271	2.670
x6	0.9402	0.145	6.484	0.000	0.656	1.225
x7	0.4729	0.132	3.585	0.000	0.214	0.732
x8	0.6313	0.173	3.648	0.000	0.292	0.971
x9	0.0334	0.158	0.212	0.832	-0.276	0.342
x10	0.1214	0.179	0.677	0.498	-0.230	0.473
x11	0.6663	0.206	3.242	0.001	0.263	1.069
x12	-0.1109	0.439	-0.252	0.801	-0.972	0.751
x13	0.6142	0.219	2.801	0.005	0.184	1.044
x14	0.9161	0.282	3.252	0.001	0.363	1.469

Omnibus:	11.202	Durbin-Watson:	2.003
Prob(Omnibus):	0.004	Jarque-Bera (JB):	12.528
Skew:	-0.151	Prob(JB):	0.00190
Kurtosis:	3.341	Cond. No.	1.28e+17

Source: Crunchbase

Graph 7: OLS Regression Model



Source: Crunchbase

Table 13: OLS Regression Results Table

OLS Regression Results

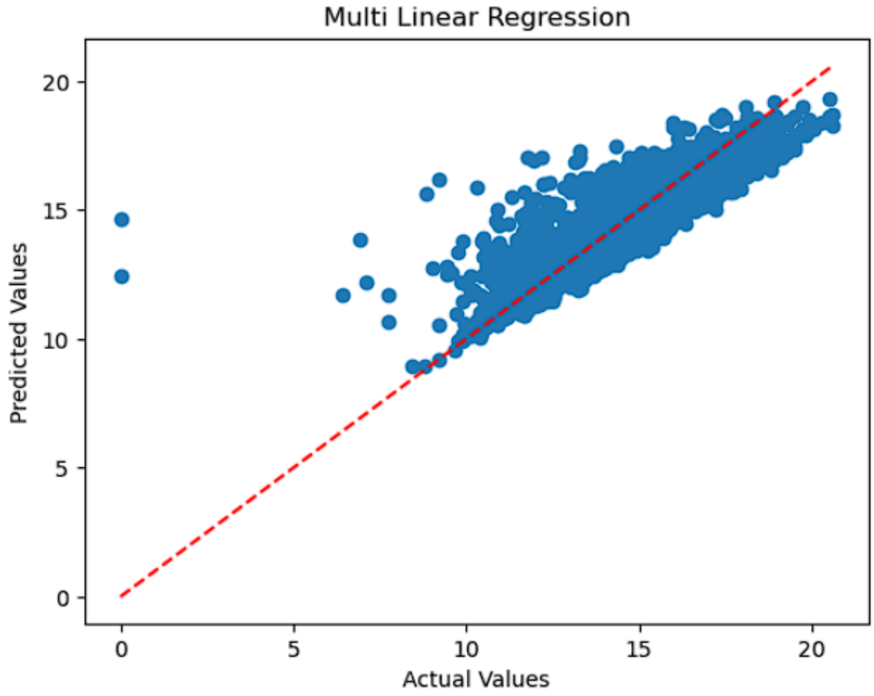
Dep. Variable:	LN (Money Raised Currency (in USD))	R-squared:	0.674
Model:	OLS	Adj. R-squared:	0.672
Method:	Least Squares	F-statistic:	315.6
Date:	Sat, 08 Jul 2023	Prob (F-statistic):	0.00
Time:	11:21:46	Log-Likelihood:	-3235.2
No. Observations:	1998	AIC:	6498.
Df Residuals:	1984	BIC:	6577.
Df Model:	13		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	3.4171	0.338	10.117	0.000	2.755	4.079
x1	0.1186	0.076	1.552	0.121	-0.031	0.268
x2	0.0954	0.061	1.557	0.120	-0.025	0.216
x3	0.1802	0.090	1.997	0.046	0.003	0.357
x4	0.6199	0.102	6.089	0.000	0.420	0.820
x5	0.3709	0.138	2.683	0.007	0.100	0.642
x6	0.9076	0.185	4.899	0.000	0.544	1.271
x7	1.1246	0.222	5.061	0.000	0.689	1.560
x8	0.2011	0.077	2.626	0.009	0.051	0.351
x9	0.6808	0.019	36.372	0.000	0.644	0.718
x10	2.3507	0.477	4.932	0.000	1.416	3.285
x11	-0.0622	0.210	-0.296	0.767	-0.474	0.349
x12	0.2915	0.319	0.914	0.361	-0.334	0.917
x13	0.6386	0.305	2.096	0.036	0.041	1.236
x14	-0.3127	0.356	-0.877	0.380	-1.012	0.386

Omnibus:	1224.757	Durbin-Watson:	1.856
Prob(Omnibus):	0.000	Jarque-Bera (JB):	27516.443
Skew:	-2.469	Prob(JB):	0.00
Kurtosis:	20.497	Cond. No.	1.19e+16

Source: Crunchbase

Graph 8: OLS Regression Model



Source: Crunchbase

Table 14: OLS Regression Results Table

OLS Regression Results

Dep. Variable:	LN (Money Raised Currency (in USD))	R-squared:	0.670
Model:	OLS	Adj. R-squared:	0.667
Method:	Least Squares	F-statistic:	268.0
Date:	Sat, 08 Jul 2023	Prob (F-statistic):	0.00
Time:	11:17:33	Log-Likelihood:	-3248.0
No. Observations:	1998	AIC:	6528.
Df Residuals:	1982	BIC:	6618.
Df Model:	15		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
const	2.4370	0.254	9.577	0.000	1.938	2.936
x1	-0.0296	0.211	-0.140	0.889	-0.444	0.385
x2	0.4858	0.320	1.518	0.129	-0.142	1.113
x3	0.6975	0.307	2.272	0.023	0.095	1.300
x4	-0.2587	0.359	-0.721	0.471	-0.963	0.445
x5	0.4154	0.081	5.120	0.000	0.256	0.575
x6	0.3293	0.064	5.108	0.000	0.203	0.456
x7	0.3366	0.106	3.179	0.001	0.129	0.544
x8	0.1841	0.089	2.080	0.038	0.011	0.358
x9	0.2513	0.104	2.411	0.016	0.047	0.456
x10	0.2630	0.137	1.917	0.055	-0.006	0.532
x11	-0.3672	0.273	-1.343	0.179	-0.903	0.169
x12	0.3471	0.136	2.545	0.011	0.080	0.615
x13	0.6774	0.200	3.387	0.001	0.285	1.070
x14	0.2210	0.077	2.869	0.004	0.070	0.372
x15	0.7339	0.013	58.268	0.000	0.709	0.759
x16	2.3688	0.480	4.930	0.000	1.426	3.311

Omnibus:	1216.006	Durbin-Watson:	1.846
Prob(Omnibus):	0.000	Jarque-Bera (JB):	26920.938
Skew:	-2.448	Prob(JB):	0.00
Kurtosis:	20.303	Cond. No.	2.58e+16

Source: Crunchbase

Table 15: GLM Regression Results Table

Generalized Linear Model Regression Results

Dep. Variable:	LN (Money Raised Currency (in USD))	No. Observations:	1998
Model:	GLM	Df Residuals:	1992
Model Family:	Poisson	Df Model:	5
Link Function:	Log	Scale:	1.0000
Method:	IRLS	Log-Likelihood:	-4658.5
Date:	Tue, 04 Jul 2023	Deviance:	334.20
Time:	21:12:09	Pearson chi2:	305.
No. Iterations:	4	Pseudo R-squ. (CS):	0.1549
Covariance Type:	nonrobust		

	coef	std err	z	P>|z|	[0.025	0.975]
x1	0.0647	0.002	37.560	0.000	0.061	0.068
x2	0.4960	0.106	4.687	0.000	0.289	0.703
x3	0.0578	0.003	17.346	0.000	0.051	0.064
x4	-0.0107	0.003	-4.126	0.000	-0.016	-0.006
x5	0.0062	0.002	2.883	0.004	0.002	0.010
x6	-0.0020	0.000	-6.995	0.000	-0.003	-0.001

Source: Crunchbase