The Valuation Game: An Empirical Study of Portuguese Startups' Success Factors

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Abstract

Valuing startups is a complex task, as these companies often have limited financial history and uncertain future cash flows. In addition, startups are typically high-risk ventures, requiring valuation techniques that consider this higher level of risk. In this study, I examine the impact of some factors in the valuation of Portuguese startups. To do this, I developed a multiple linear regression model and created nine hypotheses on the effects of each variable on valuations. The study is based on a Portuguese startup sample and uses multiple regression analysis to test the hypotheses. The study results provide insights into the factors most important in the valuation of Portuguese startups and can inform the development of more effective valuation techniques for these companies. The factors that were found to increase valuations included having a B2B focus, having a headquarters outside of Portugal, having a SaaS business model, having registered patents, and being a Fintech company. It was also found that having a female founder or attending a top university was associated with higher valuations. However, having prior startup experience or investing in R&D did not positively impact valuations.

Keywords: Venture capital; Valuation; Pre-money valuation; Startup valuation; Investment criteria; Decision-making process; Screening criteria

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Sumário

A valorização de startups é uma tarefa complexa, uma vez que estas empresas têm frequentemente uma história financeira limitada e fluxos de caixa futuros incertos. Além disso, as startups são tipicamente empreendimentos de alto risco, exigindo técnicas de avaliação que consideram este nível de risco mais elevado. Neste estudo, examino o impacto de alguns fatores na avaliação de startups portuguesas. Para tal, desenvolvi um modelo de regressão linear múltipla e criei nove hipóteses sobre os efeitos de cada variável nas avaliações. O estudo baseia-se numa amostra inicial portuguesa e utiliza a análise de regressão múltipla para testar as hipóteses. Os resultados do estudo fornecem informações sobre os fatores mais importantes na avaliação das empresas portuguesas em fase de arranque e podem ajudar no desenvolvimento de técnicas de avaliação mais eficazes para estas empresas. Os fatores que se verificou aumentarem as avaliações incluíram ter um foco B2B, ter uma sede fora de Portugal, ter um modelo de negócio SaaS, ter patentes registadas, e ser uma empresa Fintech. Verificou-se também que ter uma fundadora (sexo feminino) ou frequentar uma universidade de topo estava associado a avaliações mais elevadas. Contudo, ter experiência prévia de criação de startup ou investir em I&D não teve um impato positivo nas avaliações.

Palavras-chave: Capital de risco; Avaliação; Avaliação pre-money; Avaliação de startup; Critérios de investimento; Processo de tomada de decisão; Critérios de triagem

Título: O Jogo da Avaliação: Um Estudo Empírico dos Fatores de Sucesso das Startups Portuguesas

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List of Abbreviations

Abbreviations	Definition
ADR	American Depositary Receipt
ANI	Agência Nacional de Inovação
B2B	Business-to-Business
B2C	Business-to-Consumer
COVID-19	Coronavirus Disease 2019
ETF	Exchange Traded Fund
GAMAN	Apple, Microsoft, Alphabet, Meta and Amazon
HQ	Headquarter
IPO	Initial Public Offering
IXIC	Nasdaq Composite Index
LP	Limited Partner
OLS	Ordinary Least Squares
R&D	Research and Development
SaaS	Software-as-a-Service
SIFIDE	Sistema de Incentivos fiscais à Investigação e Desenvolvimento Empresarial or Tax Incentive System for Business Research and Development
VC	Venture Capital or Venture Capitalist
VIF	Variance Inflation Factor

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1. Introduction

"Venture capital valuation is more art than science, and it's more like a painting than a photograph. It's not easy to do, but it's gratifying when you get it right." - Marc Andreessen, co-founder of Andreessen Horowitz and co-founder of Netscape.

Working in venture capital (VC), I learned that valuations are often subjective and can vary greatly depending on the perspective of the individual or firm performing the valuation. This is because the value of an asset, such as a startup company, is not an inherent property of the asset itself but rather is determined by its perceived potential to generate future cash flows. As a result, the value of an asset can be influenced by a wide range of factors, such as the perceived strength of the company's management team, the potential size of its addressable market, or the level of competition in the industry. Because these factors are often difficult to quantify and can be influenced by personal biases and beliefs, valuations can be highly subjective, especially when there is a lack of financial data to support the decision. This makes it difficult to apply techniques like discounted cash flow analysis, which relies on accurate predictions of future cash flows. Instead, alternative techniques that are more flexible and less reliant on detailed financial projections may be more appropriate for startups.

Startups are often high-risk ventures. According to the Risk-Return Trade-off Theory, investors are willing to pay a higher multiple for the potential returns from a successful startup compared to a mature company with more predictable cash flows. As a result, valuation techniques that consider the higher risk associated with startups may be more appropriate.

Overall, adapting standard valuation techniques for startups is essential to accurately reflect the unique characteristics of these companies and provide investors with a more realistic assessment of their value.

There is no one-size-fits-all approach to valuing startups; however, according to the literature on the subject, some of the most important criteria when valuing a startup include:

1. The potential market size and growth of the startup's product or service: Determines the potential revenue and profitability of the startup.
2. The competitive landscape and the startup's competitive advantage: Determines the startup's potential market share and profitability.
3. The quality and experience of the startup's management team: Influences the ability of the startup to execute its business plan and achieve its goals.

4. The stage of development of the startup and its future funding needs: Determines the level of risk associated with the startup and the potential returns for investors.
5. The terms and conditions of any financing deals, including the startup's valuation: Determines the potential return on investment for investors.

Overall, valuing a startup requires a thorough analysis of these and other factors, and the appropriate valuation techniques and criteria will depend on the specific circumstances of the startup.

Therefore, the purpose of this dissertation is to report on the results of an empirical investigation into whether startup characteristics—inherent or not—will affect its valuation, with the ultimate goal of developing a model that might serve as a complement to the current valuation techniques employed by VCs, by detailing which are the most critical factors a VC should look at while scouting new possible investment opportunities.

From this fundamental premise, nine hypotheses were created on the impacts of startup characteristics and founder effects.

All of the assumptions are supported by statistical analyses based on a sample of 188 new enterprises as well as a sub-sample of 118 startups – excluding all companies launched during two atypical economic periods (the 2009 Portuguese financial crisis and the coronavirus disease 2019 (COVID-19) pandemic) -, showing that startups and founder characteristics can be effective in explaining venture capitalists' valuation of early-stage new initiatives. Moreover, when traditional valuation procedures are unreliable due to a lack of accounting information, this empirical connection between the selected variables and new venture valuation practice should hold some hope for investigating complementary valuation methods for new ventures.

This study is structured as follows: the Introduction provides background information about valuation and the importance of understanding the factors that impact the valuations of startups. Next, the Literature Review discusses the relevant research on startup valuations and the important variables. The Methodology section describes the data and methods used in the study, including the sample and variables selected, and the model estimation and descriptive statistics. Finally, the Results section presents the study's findings, and the Conclusion discusses the implications of the results and suggests areas for further research.

2. Literature Review

Venture Capitalists (VCs) have a great responsibility in identifying innovative and valuable opportunities. A firm's potential can be measured both quantitatively and qualitatively, which are methods that have been proven to be subjective, especially when it comes to early-stage companies. According to Dhochak et al. (2016), determining the new venture's economic value has proven to be one of the most challenging tasks in the decision-making process for VCs.

VC firms have a real positive impact on the companies they invest in. For example, Chemmanur et al. (2011) showed that the overall efficiency of VC-backed firms is higher than that of non-VC-backed firms at every point in time. This is mainly due to two key steps integrating the VC's processes: screening and monitoring. During the screening of opportunities, VCs tend to choose firms that already show signs of efficiency, hence why the growth in efficiency after the VC investment is also more significant than non-VC-backed firms.

Even though VC-supported businesses survive at a significantly higher rate than projects funded by other sources - ranging from about 65% (Sahlman 1990) of the whole VC's portfolio -successful VC-backed firms still manage to fail at giving an appropriate return to the VC (Ruhnka et al., 1992). As per Dean & Giglierano (1990), just 42% of VC-backed enterprises show a 15% return on investment (ROI), indicating a failure probability of close to 60%.

The VC's process has been shown to include many steps, ranging from scouting new opportunities to disinvestment in such companies - commonly called "exits". Authors such as Paul Gompers and Joshua Lerner call this process "The Venture Capital Cycle".

Tyebjee & Bruno (1984) proposed five stages that compose the VCs process model. These include (1) deal origination - identifying potential investment opportunities; (2) deal screening - sorting through prospective deals to invest only in a fraction of those. VCs will usually invest in areas with which they are familiar (technology, product, and market wise); (3) deal evaluation – more in-depth due diligence to weigh out risk and return; (4) deal structuring – negotiating and mutually establishing VC investment agreement terms and (5) post-investment activities – the VC moves from investor to collaborator by providing value-added activities, through representation on the board of directors or networking skills.

Although finding promising opportunities is a fundamental step to a profitable path. However, it is essential to look out for the portfolio companies after the deal has been closed, making sure they grow profitable and valuable. According to Gorman & Sahlman (1989), post-investment activities, such as assisting and monitoring one venture investment, take over 60% of a VC's time.

Despite post-investment operations taking up most of a VC's time and effort, these will only guarantee a positive outcome if the proper due diligence is correctly done beforehand. According to a study by Roure & Keeley (1990), the information gathered from a business plan can distinguish between success and failure. Therefore, venture capitalists should use their time to better understand how they make decisions and enhance their decision-making process, as this may provide them with higher returns (Zacharakis & Meyer, 2000). Often, better thought-out investment decisions lead to successful deals.

It is important to note that these "thought-out investment decisions" - i.e. the screening criteria to evaluate a new venture - will be adapted according to the type of industry, geographic location, stage, and investment size (Sorenson & Stuart, 2001). While VCs differentiate investment criteria with different objectives, the primary categories are the entrepreneur's characteristics, product, competitive strategies, market size, and growth. Still, the primary difference is how criteria are weighted differently.

In the Handbook of Research of Venture Capital, Andrew Zacharakis and Dean A. Shepherd stated:

> *"A venture capitalist interested in biotechnology will look at criteria differently than venture capitalists interested in retail; proprietary protection may be of more importance, for instance. Likewise, venture capitalists focused on early-stage deals may emphasise the team – can the entrepreneur execute on the opportunity – since there is little history of the venture to evaluate. Later stage venture capitalists can assess the team's capabilities based upon what the venture has achieved in its earlier stages."*

On the other hand, research by Monika & Sharma (2015) showed that while VCs with different investment theses look at different criteria, basic categories are still common: entrepreneur's characteristics, product, market size and growth, and competition. The main difference here is the importance they attribute to each one.

VCs have proven to be successful in their investment decisions more than once (Hall & Hofer 1993; Sandberg et al. 1987), hence why numerous studies have been trying to assess how their decision-making process is done. Early studies began by producing lists of criteria used by VCs when evaluating a new opportunity. For example, Tyebjee & Bruno (1984) gathered four main categories: market potential, management, competition and product feasibility. Also, MacMillan et al. (1985) came up with six main categories: entrepreneur's personality, experience, product/service, market characteristics, financial considerations and venture team (the initial team that composes the startup). Both these studies concluded that the entrepreneur and team are the two most valued factors considered by VCs. MacMillan et al. (1987) represent one of the first attempts to test if the criteria identified in previous studies (mainly in MacMillan et al. 1985) were indeed helpful in distinguishing between successful and unsuccessful ventures. An important finding of their research, identified through regression analysis, was that the two primary criteria predictors of venture success are: (1) the extent to which the venture is initially insulated from competition and (2) the degree to which there is demonstrated market acceptance of the product. Khan (1987) also conducted research in this area. His results showed that VCs emphasise the entrepreneurs' desire to succeed and the uniqueness of the product as an essential variable in arriving at their judgement. This study also suggests that VCs' judgements are poor predictors of actual outcomes and that derived models outperform VCs' judgements.

Nevertheless, this early approach to understanding a VC's decision process was realised to be prone to recall as well as rationalisation biases, as the VCs are not making real-time investment decisions but thinking about how they believe they used the criteria listed on past decisions.

To overcome the drawbacks mentioned above, more studies were conducted. This time using verbal protocols[1]. Verbal protocols brought some advantages when compared to previous methods, namely: (1) remove recall and rationalisation biases since VCs no longer had to introspect about their thought process; (2) "provide a richer understanding of the decision process whereas post hoc methods focus on the decision outcome (Hall & Hofer, 1993)"; (3) make it possible to understand the relative importance of each criterion used, since it not only focuses on gathering the criteria used by also in which order and preference it is used as well as the amount of time each criterion requires.

Even though verbal protocols carry many advantages, it is also essential to weigh the disadvantages of such methods. Although this approach can provide more intel and richer data than previously used techniques for data collection, it is (1) more time-consuming, meaning the sample size for these studies is usually smaller and (2) a retrospective reporting which implies

[1] Verbal protocols are real time experiments where venture capitalists 'think aloud' as they are screening a business plan (Ericsson and Crutcher, 1991).

that the conclusions are based on questionnaire responses rather than actual evaluations (Silva, 2004).

Through verbal protocols, Wells (1974) found that management commitment is the criteria they emphasise when VCs consider an investment proposal. This criterion was closely followed by product, market, and marketing skills. Poindexter (1976) also contributed to the same conclusion, finding that the quality of management was the criterion with the highest rank in the opinion of VCs. The expected rate of return and expected risk followed.

Verbal protocol studies have found that VCs prioritise the entrepreneur and team less and strategic issues even less when evaluating a new venture proposal. However, these results contradict those of Tyebjee & Bruno (1984) and MacMillan et al. (1985). One possible explanation for this discrepancy is that the focus of verbal protocols may differ at the opportunity's screening stage. Researchers have turned to conjoint analysis to address this inconsistency and small sample sizes. Conjoint analysis is a technique that allows researchers to analyse the decision-making process of respondents by presenting them with profiles that they must evaluate. It can be defined as a method to quantitatively capture the relative importance of a list of attributes compared to each other (Muzyka et al. 1996). In a study using this technique, Muzyka et al. (1996) found that all five management team criteria were ranked highly by VCs: (1) the leadership potential of the lead entrepreneur; (2) the leadership potential of the management team; (3) the presence of recognised industry experts in the team; (4) the track record of the lead entrepreneur; and (5) the track record of the management team. Riquelme & Rickards (1992) also found that VCs strongly emphasise the entrepreneur's experience. Conjoint studies (Zacharakis & Meyer, 1998) support verbal protocol research (Hall & Hofer, 1993), indicating that market issues might be more critical than entrepreneur characteristics. The more factors a decision maker must weigh, the less accurate introspection becomes (Zacharakis & Meyer, 1998). This might explain why real-world studies have shown that VCs frequently overvalue less significant elements and undervalue more critical ones (Zacharakis & Meyer, 1998; Shepherd, 1999) since, as a result, information perceived as more outstanding is remembered as more significant than it was, in the decision-making process.

Conjoint analysis is essential to understand the VC decision-making process (Shepherd & Zacharakis, 1999).

Thus, the study of venture capital decision-making has progressed naturally from defining criteria through post hoc surveys (e.g. Tyebjee & Bruno, 1984; MacMillan et al., 1985) to comprehending how that information is used during the actual decision through verbal protocols (e.g. Sandberg et al., 1989; Hall & Hofer, 1993) to controlled experiments that can highlight similarities and differences between venture capital decision-making (Shepherd et al., 1999; Zacharakis & Shepherd, 2005).

Silva (2004) points out that while the majority of earlier studies have examined the VCs' decision-making process in large and developed private equity markets, only a minimal number of studies have looked into the subject in geographies where the private equity industry does not yet represent a clear alternative source of funding for businesses.

While there has been much research on the investment decision process of VC, more needs to be done regarding the impact of specific characteristics on the valuation of startups.

This research follows the approach of Miloud et al. (2012), where the authors seek to link previous studies with this under-investigated area of venture capital while exploring the possibility of developing a complementary method to value startups, particularly early-stage, where little data is disclosed, focusing on the French startup ecosystem.

According to Shepherd (1999), “helping venture capitalists better understand their decision-making process, which, in turn, provides the opportunity to increase evaluation efficiency”.

3. Data and Methodology

3.1. Data

This study aims to report on the findings of empirical research on whether specific characteristics - inherent or not - of a startup will affect its valuation, ultimately aiming to develop a multiple linear regression model that can work as a complement to the current valuation methods being used by VCs, focusing on a more qualitative approach, by detailing which are the most critical factors a VC should look at while scouting new possible investment opportunities.

Most research that sought to understand the VC decision-making process relied heavily on questionnaires, which had certain drawbacks covered in length in the previous section, "Literature Review".

Since most startup companies are private and very reluctant to disclose objective financial information, there are limited resources and data available, particularly regarding metrics like valuation or round information, *inter alia*. This made using a sound database for the sole purpose of this study a difficult process. Additionally, because some startups are very early stage, the reliability of the data is also a significant concern, which is why finding the right database, in this case, Dealroom, was a pressing issue.

The primary data sample, all startups in Portugal, were gathered from Dealroom[2], in collaboration with Startup Portugal, containing all Portuguese startups launched between 1990 and late 2022. Dealroom is one of the biggest and most credible data providers on startups, growth companies and tech ecosystems. It combines machine learning as well as data engineering with extensive verification processes to gather data from public sources such as news, company filings, domain & trade registries, job boards, web and app store analytics and investor portfolios, among others, making it a trustworthy source for creating the database used in this study.

The sample includes - as of the date it was retrieved - 2,023 companies regardless of the industry, stage, and client focus (either Business-to-Business (B2B) or Business-to-Consumer (B2C)).

[2] https://startupportugal.dealroom.co/

This data was used in all the following tables and analyses, with additional changes to the dataset, if applicable, mentioned in the respective parts of this dissertation.

Only companies with information for all the variables chosen for this study would be considered from the primary sample. After excluding all businesses without enough data, the final dataset covered a total of 188 observations over the period from 2000 until 2022.

The specific dataset used in this dissertation is a cross-sectional dataset, which consists of observations for multiple units of analysis at a single point in time. In contrast to panel datasets, which consist of repeated observations for the same units of analysis over time, cross-sectional datasets provide a snapshot of the units of analysis at a single point in time.

3.2. Variables

3.2.1. Dependent Variable

As stated by Miloud et al. (2012), "for venture capitalists, the valuation is important because the value of the company determines the proportion of the shares they receive in return for their investments, guides the overall profitability of their fund, and thus also affects their relationship with their Limited Partners (LP)[3]. Likewise, the valuation is important for the entrepreneur as it governs the motivation and sets a value to the efforts and resources he puts into his new venture".

Still, as most founders have difficulty "naming their price," valuation is frequently somewhat arbitrary in computing because there is no set standard for how many shares a company should sell. This is why valuation methodologies are vital in the valuation process, given that the final valuation range for the rounds is inferred from those.

Also, as Manigart et al. (1997) mentioned, VCs' required return levels will vary across countries. For example, according to their sample, Belgian and Dutch VCs seek the lowest necessary returns, whereas United Kingdom VCs expect more significant returns than their French counterparts. This suggests that VCs from the United Kingdom should value businesses less highly than those from France, Belgium, and Holland.

[3] Investors (individual or corporate entities) that commit capital to the venture capital fund in exchange for profits, as well as, access to information and future deal opportunities. These are commonly high net worth individuals, pension funds, family offices, sovereign funds and insurance companies.

Because it is such a key yet subjective measure, “Pre-Money Valuation” - given by the pre-money valuation in millions - was chosen as the dependent variable in this study.

The database provided only the post-money valuation based on either: (i) publicly disclosed value or (ii) an estimate based on the last funding round amount, using similar rounds as benchmarks. To get to the pre-money valuation for each observation, the money invested at the last financing round was subtracted from the announced amount of valuation, which is a common practice in the literature on VC investment, according to author Gompers (1995). When a range for the valuation was provided in the database, the average value between the minimum and the maximum values within the range would be assumed as the final post-money valuation. For the cases where no post-money valuation was disclosed, a dilution of 20% from the last financing round was assumed to get a proxy for the pre-money valuation, allowing for a bigger sample size. This assumption is in line with YCombinator - a renowned American technology startup accelerator - which recommends that companies sell 10-15% in a seed round and 15-25% in a Series A round. Additionally, according to an article written by Mark Suster and published by TechCrunch in 2011, the industry norm for dilution in a VC financing round is around 20%.

A Shapiro-Wilk W test was performed to see whether the dependent variable was normally distributed. The result showed that the variable "pre-money" does not follow a normal distribution. Therefore, the log transformation of the data was required to resolve this problem, and the startup company’s pre-money valuation is now measured using the log of the pre-money valuation.

3.2.2. Control Variables

As previously noted, valuation is a challenging process that can be impacted by various factors from inside and outside the organisation. Therefore, it is crucial to account for factors that might not have a direct bearing on valuation but do have an impact on how other independent variables selected for this study affect it.

All selected control variables were already included in the original sample, taken from Dealroom, except for the stock index chosen, Nasdaq Composite Index, which was retrieved from Refinitiv Eikon’s Datastream tool for Excel.

Below is a detailed explanation of each variable used:

1. *Nasdaq Composite Index* – The monthly closing prices in millions, from 2000 to 2022, of the index at the last funding round dates of each company in the sample.

Research has shown that public markets positively impact private market valuation. For instance, Gompers & Lerner (1999) found that the average valuation in the venture capital market increases by 26% for every doubling of capital injection into the public capital market. Additionally, Lerner (1994), Hand (2005) and Hand (2007) found that the stock valuations of publicly traded biotech companies had a favourable impact on the valuations of private biotech enterprises, suggesting that the potential profitability of a startup is reflected in the valuations of publicly traded companies.
To control for this effect, the closing prices were gathered and matched with the last funding date of each company in the dataset.
Of all the technology-focused stock indexes, Nasdaq Composite Index was selected. The Nasdaq Composite (IXIC) is an index that tracks the performance of more than 3,000 stocks listed on the Nasdaq exchange. To be listed on the exchange (and therefore be included in the composite), a stock must be listed exclusively on the Nasdaq stock exchange and common stock of a domestic company or an American Depositary Receipts (ADR) of a foreign company. No preferred stocks or exchange-traded funds (ETFs) are included in the index. Since there is a high concentration of technology firms listed on the Nasdaq stock exchange, the Nasdaq Composite is generally considered a stand-in for the performance of the overall tech industry. It includes big technology companies like the well-known Big Five or GAMAN (Apple, Microsoft, Alphabet, Meta and Amazon). Tech companies make up about 50% of the index, consumer services companies are about 20%, and healthcare companies constitute about 10%. The remaining companies are in stock sectors like utilities, oil and telecommunications.

Similarly to what was done to the dependent variable, a Shapiro-Wilk W test was performed to see whether the variable was normally distributed. The result showed that the variable does not follow a normal distribution. The log transformation of the data was required to resolve this problem, and the closing prices are now measured using the log of the pre-money valuation.

a. *Firm Age* - Variable given by the difference, in months, from the launch date of a startup and the current date (assumed to be November 1st, 2022).

Financing round generally covaries with firm age. For example, Sievers et al. (2013) find that in Germany, firm age is insignificant in explaining startup valuations, implying that conducting a new financing round is more informative than a startup's age. However, the finding stands in contrast to that of Armstrong et al. (2006), who, while also controlling for funding series, find that age is significant and negatively related to valuation among US startups. Armstrong et al. (2006) speculate that this might be rooted in VCs' time-to-exit rationale, as a longer time-to-exit is associated with lower returns.

b. *Developmental Stage* - Variable that distinguishes the company regarding its stage in the firm's lifecycle.

The lifecycle of the firm can be distinguished between seed, early growth, and late growth, which were already predefined in the original database, through the following criteria:

(i) Seed can be defined as a company with less than ten people and/or less than €1 million in funding.
(ii) Early growth can be defined as a company with between 11 and 50 people and/or between €1 and €10 million in funding or post-series A.
(iii) Late growth can be defined as a company with over 50 people and/or over €10 million in funding.

These investment stages have been found to differ regarding their key characteristics, developmental goals and significant developmental risks (Ruhnka & Young, 1987; Flynn & Forman, 2001).

Seed financing involves a small amount of capital provided to an entrepreneur to prove a concept (Sohl, 1999; Branscomb & Auerswald, 2002) before an actual product or company is organised. Ruhnka & Young (1987) found that characteristic of the seed stage is the existence of a mere idea or a concept and the absence of a management team beyond the founder and one or more technicians. Therefore, the critical goals for the seed stage include producing a product prototype and demonstrating technical feasibility, as well as conducting a preliminary market assessment.

Startup financing provides funds for product development and initial marketing. In the startup stage, the investigation of the feasibility of the business concept has generally progressed to the point of having a formal business plan together with some analysis of the market for the proposed product or service. Major benchmarks for this stage include establishing the business concept's technological, market and manufacturing feasibility (Ruhnka & Young, 1987). The first stage of financing provides funds to initiate commercial manufacturing and sales. The first stage is characterised by having an entire management team in place, a market receptive to the product, a need for a ramp-up of the production process, and the existence of a ready prototype for the market (Ruhnka & Young, 1987; Sahlman, 1990; Sohl, 1999; Branscomb & Auerswald, 2002).

Even though there exists less consensus on the typical characteristics of the ventures in the later stages of their development (Ruhnka & Young, 1987), it is possible to distinguish more mature portfolio companies from early-stage investments. As later-stage investment targets have already established their market presence, their key developmental goals include achieving market share targets and reaching profitability to enable venture capitalists to exit the investment successfully. Furthermore, compared to early-stage ventures struggling with product, market and organisation development challenges, later-stage investments face the threat of technological obsolescence and unanticipated competition caused by new entrants (Ruhnka & Young, 1987; Branscomb & Auerswald, 2002).

c. *Acquisition Status* - Variable that distinguishes between companies acquired and non-acquired.

According to Andrew Zacharakis and Dean A. Shepherd's Handbook of Research on Venture Capital, VCs frequently invest with a successful exit strategy in mind and a 4–7-year time horizon (venture capitalists are typically committed to returning to their LPs their principal and earnings within 8–10 years). Successful ventures usually have an Initial Public Offering (IPO) or acquisition as their exit strategy. The failure of an experience usually results in bankruptcy and closure or in a precarious existence from which the venture capitalists eventually divest themselves (these ventures are often referred to as the "living dead"). For instance, Busenitz et al. (2004) employed the four unique categories of IPO, acquisition, living dead, and out-of-business as their performance variable. More recently, Dimov & Shepherd (2005) contrasted IPO firms with those that went bankrupt as their dependent variable. Because venture capitalists invest with an exit in mind and a short time horizon, this performance indicator has powerful potential. These results offer four rather distinct and perceptible changes in organisational status, but they come with certain limitations. The IPO market is undoubtedly cyclical, with only the finest companies occasionally going public, as was the case in the early to mid-2000s. Other times, like in the late 1990s, certain businesses with relatively subpar performance were permitted to go public. The fluctuations in the value assigned to acquisitions are influenced by the IPO cycles. Furthermore, as such an exit may occasionally be employed to liquidate a business, there can be some variation in the value of an acquisition. Hence, it is crucial to use the "Acquisition Stage" variable to understand the valuations in the sample.

d. Number of Employees – The company's size is measured using the number of employees as a proxy.

This strategy to get the size of the company is backed up by Lee & Zhang (2011). Those authors discovered that the number of employees could be used as a proxy for a firm's development stage and the organisation's degree of risk. Furthermore, McMahon (2001) found that the company's size – measured in terms of headcount – positively impacts its performance.
For this specific variable, the initial database could only provide a range for the number of employees for each company. To overcome this issue, the average between the minimum and maximum values of the range of employees for each company was assumed to be the final number of employees. However, this poses a limitation; thus, the results might be skewed.

3.2.3. Independent Variables

In this research, the independent variables included were divided into three categories: Startup Characteristics, Founder Effects and Performance Metrics.

3.2.3.1. Startup Characteristics

a. *Client Focus* – Variable that categorises the companies in the sample according to their business model: B2B, both B2B and B2C and B2C.

H1 - The B2B focus positively affects a startup's valuation

b. *Headquarters' (HQ) Location* – Variable that separates companies with headquarters in Portugal from those outside Portugal.

H2 - Having HQ in Portugal positively affects a startup's valuation

Location is a critical factor that VCs take into consideration when scouting opportunities. However, this variable means understanding if HQ location can also significantly impact the pre-money valuation of a company. Mason (2007) stated that long-distance investments are typically more appealing to investors who have industry-specific investment preferences. When this happens, investors are usually more willing to invest in opportunities, despite their geographic location.

c. *Business Model* – Variable that distinguishes the companies in the sample regarding their business model: SaaS (Software-as-a-Service), Manufacturing and Marketplace.

H3 - A SaaS business model positively affects a startup's valuation

According to previous studies, startups operating in different industries yield different valuation ranges. Therefore, the goal of this variable is to identify if the same happens for the business model. The three business models analysed are SaaS, manufacturing or marketplace & e-commerce - predefined categories already assigned by Dealroom to each startup.

A SaaS business model tries to give consumers access to software hosted on a cloud infrastructure and used through a web browser in exchange for a monthly charge. A very successful example in the analysed sample is OutSystems - a Portuguese low-code platform allowing its users to build enterprise apps with little expertise.

The second type of business model, manufacturing, refers to companies that use raw materials to create a product to sell.

Finally, marketplace & e-commerce designates two types of online store businesses that can be used as one or independently. The main difference between an e-commerce and a marketplace business is that the first supports only a single seller. At the same time, the latter enables multiple sellers to offer products through the same platform. This study's excellent example of an e-commerce & marketplace business includes Farfetch, an online luxury fashion retail platform.

d. *Intellectual Property* – Variable that distinguishes the startups in the sample between having at least one registered patent or not.

H4 - Having registered patents positively affects a startup's valuation

According to previous literature, e.g. Block et al. (2014), intellectual property is significant to VCs as it can, among other things, further reduce asymmetric information.

There is also extensive literature, e.g. Lerner (1994), that shows that the number of patents positively affects the pre-money valuation of a startup. In later studies, Hand (2005) also relating to biotech startups, Armstrong et al. (2006) across industries, and Hsu & Ziedonis (2013) for 370 semiconductor startups, are consistent in finding that the number of patent applications filed is associated with higher startup valuations. On the other hand, Hand (2005) reports that patents' value relevance is remarkably low on a round-by-round basis. In contrast to Lerner (1994), the same study identifies a significant negative relationship and reports that patents' value relevance is remarkably low on a round-by-round basis.

Given this inconsistency, this variable will identify whether patents positively or negatively impact pre-money valuations in the Portuguese reality.

e. *Fintech* - Variable that assesses whether fintech companies have a significant change, compared with other types of startups, regarding valuation.

H5 - Being a fintech positively affects a startup's valuation

In the particular case of the dataset used, "other types of startups" can range from enterprise software, health, marketing, food, media, real estate, energy, travel, fashion, transportation, education, gaming, home living, sports, wellness beauty, jobs recruitment, security, robotics, event tech, telecom, semiconductors, hosting, music, kids, legal, dating, space, service provider engineering and manufacturing equipment and chemicals.

According to Arner et al. (2015), "Financial technology" or "FinTech" refers to the use of technology to deliver financial solutions. These companies can act in areas like Lending, Blockchain/Crypto, Regtech, Personal Finance, Payments/Billing, Insurance, Capital Markets, Wealth Management, Money Transfer/Remittances and Mortgage/Real Estate, to name a few.

There is no historical evidence that Fintech startups receive higher valuations. Nevertheless, this variable was included to understand if such an event could occur in Portugal.

f. *Research and Development (R&D)* - Variable that identifies companies that are certified by Agência Nacional de Inovação (ANI) as being compliant with Sistema de Incentivos fiscais à Investigação e Desenvolvimento Empresarial (SIFIDE)[4], available in the List of entities recognized in the practice of Research and Development activities, thus indicating that these companies have a heavy investment in R&D.

H6 – Having high R&D investment positively affects a startup's valuation

[4] SIFIDE (Tax Incentive System for Business Research and Development), created in 1997, is a Portuguese tax benefit granted to Portuguese companies that carry out R&D activities, allowing them to recover part of the investment made and enhancing their future R&D efforts. This incentive allows for a tax deduction of up to 82.5% of the costs associated with research and development activities in the reference year. Among the main eligible expenses are personnel costs, general operating expenses, R&D activity hiring and patent registration and maintenance, among others.

R&D can be a significant factor in determining the value of a startup. This is because R&D can be an essential source of competitive advantage and lead to the development of new and innovative products or technologies. As a result, investors are generally willing to pay a higher valuation for startups that are heavily invested in R&D. This indicates that the company is dedicated to staying at the forefront of its industry and is likely to continue generating new ideas and revenue streams.

Miloud et al. (2012) identified that the R&D intensity ratio is highly significant and shows that companies with more R&D receive a higher valuation from VCs.

3.2.3.2. Founder effects

As Franke et al. (2008) claimed, the entrepreneurial team is crucial to venture investors' evaluation of a business. Also, as MacMillan et al. (1985) mentioned, VCs actively search for founder and team traits that can provide information about the calibre of a firm and affect valuation.

a. *Prior Startup Experience* – Variable that tells apart companies whose founder has previous startup experience and those who do not.

H7 - Founders with previous experience positively affects a startup's valuation

As reported in previous research, there is a connection between prior founding experience and higher valuation (Wasserman, 2016). Also, Hsu (2007) shows that entrepreneurs with previous experience in founding a startup who achieved high financial returns with their last ventures (i.e., an internal rate of return of at least 100% on Series A investments at an exit event) attract higher valuations for their new ventures.

b. *Founder Gender* – Variable that distinguishes startups with a female founder from startups with a male founder.

H8 - Founder being a female positively affects a startup's valuation

An interview conducted by Knowledge at Wharton, a business journal from the Wharton School of the University of Pennsylvania, with Ethan Mollick, a Management Professor at Wharton and author of "Humility and Hubris: Gender Differences in Serial Founding Rates", showed that in the United States of America, 40% of companies are VC funded, by of that only 2 - 4 % have female co-founders.

Also, according to Sifted, the amount of money coming to all-female founding teams in Europe decreased from 2.4% in 2020 to just 1.1% in 2021, despite fundraising rounds reaching new highs.

The goal of using this variable is to understand if the gender of the founder has any influence on the company's pre-money valuation.

c. *Founder Attended Top University*[5] – Variable that separates companies whose founder attended a top university from those who did not.

H9 - Founder attending a top university positively affects a startup's valuation

The use of this variable seeks to uncover if the fact that a founder attended a top university will ultimately be reflected in a higher valuation of their company. People who attend top universities usually have more execution capacity, thus, a higher probability of generating increased future revenues when leading a company.

Table 1 below, better presents and summarises the variables used in this study.

Table 1. *Summary of variables and measurements*

		Dependent Variable	
	premoney	Pre-Money Valuation	Announced valuation of company (in millions) - Amount invested in the last financing round (in millions)
		Independent Variables	
Control variables	ixic	Nasdaq Composite Index	The close points of IXIC, in millions, at the last financing date of each company
	age	Firm Age	The time difference, in months, between founding date and today (considered November, 1st 2022)
	stage	Development Stage	Categorical variable, coded '-1' if company's stage is "seed", '0' if stage is "early growth" and '1' if stage is "late growth"
	status	Acquisition Status	Dummy variable, coded '1' if company's status is "acquired", '0' otherwise
	size	Number of Employees	Average number of employees working at the startup
Startup characteristics	focus	Client Focus	Categorical variable, coded '-1' if focus is "B2B", '0' if focus is "B2C and B2B" and '1' if focus is "B2C"
	hq	Headquarters' Location	Dummy variable, coded '1' if the headquarters are in Portugal and '0' otherwise

[5] The concept of "top university", applied by Dealroom, although not defined by the database can be thought of as any well-respected and acclaimed university, either in Portugal or outside, where the founder has studied. Some examples could be an Ivy League school, Católica Lisbon SBE or Instituto Superior Técnico.

	bus_model	Business Model	Categorical variable, coded '-1' if business model is "manufacturing", '0' if it is a "marketplace" and '1' is it is "SaaS"
	patent	Intellectual Property	Dummy variable, coded '1' if company has patents and '0' otherwise
	fintech	Fintech	Dummy variable, coded '1' if the company is a fintech and '0' otherwise
	rd	Research and Development	Dummy variable, coded '1' if startup is certified by ANI and '0' otherwise
Founder effects	experience	Prior Startup Experience	Dummy variable, coded '1' if founder has prior startup experience and '0' otherwise
	gender	Founder Gender	Dummy variable, coded '1' if founder is a female and '0' if founder is a male
	top_uni	Founder Attended Top University	Dummy variable, coded '1' if founder attended a top university and '0' otherwise

3.3. Model estimation and descriptive statistics

To regress the model presented, Stata (version 17) was used. A linear regression was used to test the hypotheses mentioned above (research questions) and determine the relationship between the listed variables and the company's valuation, particularly an ordinary least squares (OLS) regression. The following formula can express the model:

$$Log(pre - money\ valuation)_i = \alpha_i + \beta_1 log\ (ixic)_i\ + \beta_2 age_i + \beta_3 status_i + \beta_4 stage_i + \beta_5 size_i + \beta_6 focus_i + \beta_7 hq_i + \beta_8 bus\_model_i + \beta_9 patent_i + \beta_{10} fintech_i + \beta_{11} rd_i + \beta_{12} experience_i + \beta_{13} gender_i + \beta_{14} top\_uni_i + \beta_{15} rd_i + \varepsilon_i$$

To avoid multicollinearity, some variables - initially included in the models - were taken out, e.g. level of education, the amount raised in the last funding round, time (in months) since the previous funding round and annual growth rate.

In a linear regression model, multicollinearity refers to a situation in which two or more predictor variables are highly correlated. This can cause problems in the model because it can make it difficult to determine the individual contribution of each predictor variable to the outcome and can also lead to unstable and inconsistent coefficients. In other words, multicollinearity can make it challenging to interpret the results of the regression and can reduce the model's predictive accuracy. One way to detect multicollinearity in a regression model is to calculate each predictor variable's variance inflation factor (VIF). A VIF value of 1 indicates no multicollinearity, while a VIF value greater than 10 indicates a high degree of multicollinearity. If multicollinearity is detected, it can be addressed by removing one or more of the highly correlated predictor variables from the model or using a different statistical technique less sensitive to multicollinearity.

Heteroscedasticity was another concern for this sample, hence why the pre-money valuation and the closing prices of the Nasdaq Composite Index were logged. In a linear regression model, heteroscedasticity refers to a situation in which the variability of the error term is not constant across all values of the predictor variables. This can cause problems in the model because it can make the standard errors of the coefficients inaccurate, affecting the statistical significance of the coefficients and the overall validity of the model. One way to detect heteroscedasticity in a regression model is to plot the residuals (the difference between the predicted and actual values) against the predicted values. If the residuals are evenly distributed around the zero line and have a constant spread, there is no heteroscedasticity. However, if the spread of the residuals is not constant and increases or decreases as the predicted values increase or decrease, this indicates the presence of heteroscedasticity. The strategy adopted to look for heteroscedasticity in the sample was through a Breusch-Pagan test. If heteroscedasticity is detected, it can be addressed by transforming the predictor variables or the outcome variable or using a different statistical technique less sensitive to heteroscedasticity.

Endogeneity was the last test on the sample to avoid misleading results. Endogeneity in an OLS regression refers to the situation in which one or more of the independent variables in the model are correlated with the error term. This can cause the estimated coefficients in the model to be biased and lead to incorrect conclusions being drawn from the model. Various methods can be used to avoid endogeneity, such as instrumental variables, control variables, or difference-in-differences. A fixed effects model is also a possibility, which can help to control for time-invariant unobserved variables that may be correlated with the error term. A few factors can cause endogeneity in a regression. One common cause is the presence of omitted variables[6] correlated with the independent and dependent variables. Other potential causes of endogeneity include measurement error, reverse causality, and simultaneous causality. Given that the dataset used is cross-sectional, the selected method used to avoid endogeneity was testing for omitted variables and trying to address them when possible.

[6] Omitted variables are variables that should be included in the model but are not. This can happen for a variety of reasons, such as the variable not being measured or not being available at the time the model was estimated.

This dissertation focuses only on one country - Portugal - so that all companies would be as comparable as possible since the specifics of company valuation could differ significantly across different locations. Table 2 presents the descriptive statistics of the selected sample.

Table 2. *Descriptive Statistics*

Variable Name	Variable	Obs	Mean	Std. dev.	Min	Max
Pre-Money Valuation	premoney	188	135.5437	963.1056	0.0400	9377.0000
Log of Pre-Money Valuation	log_premoney	188	0.4588	0.9338	-1.4000	3.9700
Nasdaq Composite Index	ixic	188	8.8155	4.6775	1.6100	16.5000
Log of Nasdaq Composite Index	log_ixic	188	0.8712	0.2681	0.2100	1.2200
Firm Age	age	188	84.8484	47.8502	8.1700	278.0000
Development Stage	stage	188	-0.2234	0.7335	-1.0000	1.0000
Acquisition Status	status	188	0.0957	0.2950	0.0000	1.0000
Number of Employees	size	188	255.7527	2214.4560	1.0000	30000.5000
Client Focus	focus	188	-0.3351	0.8772	-1.0000	1.0000
Headquarters' Location	hq	188	0.9149	0.2798	0.0000	1.0000
Business Model	bus_model	188	0.4415	0.7470	-1.0000	1.0000
Intellectual Property	patent	188	0.0851	0.2798	0.0000	1.0000
Fintech	fintech	188	0.0745	0.2632	0.0000	1.0000
Research and Development	rd	188	0.0691	0.2544	0.0000	1.0000
Prior Startup Experience	experience	188	0.4628	0.4999	0.0000	1.0000
Founder Gender	gender	188	0.2128	0.4104	0.0000	1.0000
Founder Attended Top University	top_uni	188	0.3351	0.4733	0.0000	1.0000

The sample for this study consists of businesses that were established between 2000 and 2022, with an average age of approximately 85 months or seven years. Their valuations range from €40 thousand to €9.38 billion, with an average valuation of €136 million. Of the companies in the sample, only 10% have been acquired. In terms of size, measured by the number of employees, the smallest company in the sample has one employee and the largest has between 5,001 and 10,000 employees, with an average size of around 256 employees. The majority of the startups in the sample (60%) focus on B2B clients, while 27% focus on B2C and 13% serve both B2B and B2C clients. Although the majority of the companies in the sample are headquartered in Portugal (91%), there are some companies with headquarters located in other countries, such as the United Kingdom, the United States, and Denmark. In terms of business model, the majority (60%) of the companies in the sample are SaaS companies, 24% operate using a marketplace model, and only 16% have a manufacturing model. Interestingly, only 9% of the companies in the sample have a registered patent. Of the overall sample, 8% are fintech companies and only 7% are considered to be research and development-intensive startups. In terms of the founding team, 46% have previous startup experience, 79% are male, and 34% come from top universities. The total amount of funding raised to date by the entire sample is more than €3 billion, with a minimum of €10 thousand raised in a seed round and a maximum of €638 billion. Additional graphical representations of this sample can be found in Chapter 6, "Appendix".

4. Results

Table 3 reports the estimates from the OLS regression on the pre-money valuation of the new ventures in the sample.

Table 3. *Models 1, 2, 3 and 4 for the log of pre-money valuation regression*

A sample of 188 companies was used for these regressions. The log of the pre-money valuation is the dependent variable (calculated by subtracting the amount invested in the last financing round to the post-money valuation of the company). Entries are the coefficients, and in parenthesis, the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. One, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

Variables Name	Stata Variables Name	(1) Control Variables Only Model 1	(2) Control Variables + Startup Characteristics Model 2	(3) Control Variables + Founder Effects Model 3	(4) All variables Model 4
Log of Nasdaq Composite Index	log_ixic	**0.485***	**0.497***	0.391	**0.466***
		(0.279)	(0.272)	(0.278)	(0.276)
Firm Age	age	**0.00307***	**0.00274***	**0.00282***	**0.00287***
		(0.00159)	(0.00156)	(0.00158)	(0.00159)
Development Stage	stage	**0.702*****	**0.632*****	**0.668*****	**0.604*****
		(0.0749)	(0.0766)	(0.0753)	(0.0768)
Acquisition Status	status	0.174	0.176	0.0700	0.0741
		(0.179)	(0.178)	(0.181)	(0.180)
Number of Employees	size	**8.36e-05*****	**6.73e-05*****	**8.88e-05*****	**7.37e-05*****
		(2.39e-05)	(2.45e-05)	(2.37e-05)	(2.44e-05)
Client Focus	focus		-0.0632		-0.0644
			(0.0608)		(0.0608)
Headquarters' Location	hq		**-0.570*****		**-0.514****
			(0.199)		(0.202)
Business Model	bus_model		-0.00822		-0.0118
			(0.0722)		(0.0722)
Intellectual Property	patent		0.282		**0.313***
			(0.190)		(0.189)
Fintech	fintech		0.172		0.188
			(0.194)		(0.195)
Research and Development	rd				-0.187
					(0.210)
Prior Startup Experience	experience			-0.0639	-0.0827
				(0.105)	(0.103)

Founder Gender	gender			0.0643	0.0265
				(0.125)	(0.128)
Founder Attended Top University	top_uni			**0.314*****	**0.308*****
				(0.114)	(0.114)
	Constant	-0.105	-0.367	-0.0908	-0.275
		(0.362)	(0.411)	(0.359)	(0.419)
	Observations	188	188	188	188
	R-squared	0.450	0.495	0.472	0.516

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

For the inference of the above-detailed variables in the pre-money valuation of a Portuguese startup, a 4-Model approach was used. Model 1 is the baseline model, which only contains the control variables, which will be used in all the following models. Model 2 tests the startup characteristics effects, and Model 3 tests the founder effects. Model 4 is the full model containing all the variables. Model 4 also has the highest explanatory power, yielding an R^2 of approximately 52%.

4.1. Control variables

Most control variables used had a slight positive and statistically significant impact, namely the Nasdaq Composite Index (log_ixic), Firm Age (age), Development Stage (stage) and Company Size (size).

On the other hand, the Acquisition Status (status) had a positive yet non-significant impact on the pre-money valuation.

4.2. Startup Characteristics

Using the startup characteristics variables, I hypothesised whether VCs consider these characteristics when valuing a company, subdividing the research into six different hypotheses.

Focusing on B2B (H1), having a SaaS business model (H3), owning patents (H4) and being a fintech (H5) seem to have a positive impact while having headquarters in Portugal (H2) and investing in R&D (H6) appears to have a negative effect of the startup's valuation.

Regarding the client focus of the startups, the results indicate that startups that are focused on B2B rather than B2C or both B2B and B2C, on average, get higher valuations. There are several reasons why a B2B (business-to-business) startup may have a higher valuation than a B2C (business-to-consumer) startup. One reason is that B2B companies often have a more predictable revenue stream because they typically have long-term contracts with their customers. This predictability can make B2B startups more attractive to investors. Another reason is that B2B companies often serve a niche market, which can make them less susceptible to competition. This can give B2B startups a competitive advantage and make them more valuable to investors. Additionally, B2B companies often directly impact their customers' operations, which can make them more valuable to their customers. This, in turn, can make B2B startups more valuable to investors. Overall, B2B startups can have a higher valuation because they often have a more predictable revenue stream, serve a niche market, and directly impact their customers' operations. However, in Portugal’s specific context, the market size of B2C companies is relatively small compared to B2B companies, which means that for an investor, the same effort will yield a smaller return, lowering the attractiveness of these deals. Plus, B2C companies are usually more cash-intensive, and the VC industry in Portugal is still taking off.

The results show that having headquarters in Portugal, on average, negatively impacts startups’ valuations with a 5% significance level. The coefficient of -0.514 suggests that, on average, when Portuguese startups have their headquarters in Portugal, their valuations decrease by 40%. The valuation of a startup can also be influenced by factors such as the state of the broader economy and the availability of funding. These factors can vary from country to country, affecting the valuation of startups in different countries. For example, a country with a strong economy and a robust ecosystem for startups, for example, the United States of America, may have higher startup valuations than a country with a weaker economy and less developed startup ecosystem, in this case, Portugal. Additionally, the specific market a startup operates in, as well as its stage of development, can also affect its valuation.

Another inference that can be drawn from the regression is that adopting a SaaS business model will, on average, positively impact the startups’ valuations in comparison with other types of business models, such as manufacturing or marketplace models. Firstly, SaaS businesses typically have a predictable and recurring revenue stream. This is because customers generally pay a subscription fee to use the software on a recurring basis, such as monthly or annually. This predictable revenue stream can make it easier for investors to forecast the future financial performance of the business and can increase the startup’s valuation. Secondly, SaaS businesses often have relatively low customer acquisition costs since the software is delivered over the internet, allowing the company to reach many potential customers at a low cost. In comparison, manufacturing businesses often have high upfront costs for things like materials, production, and distribution, which can make it more difficult for them to scale and increase their valuation, and marketplace businesses often have higher customer acquisition costs because they need to invest in marketing and other efforts to attract buyers and sellers to the platform. Finally, SaaS businesses often have a high gross margin, the difference between the cost of goods sold and the price at which the product is sold. This is because the cost of delivering software over the internet is relatively low, so a large portion of the revenue generated by the business is profit. In comparison, manufacturing businesses often have a lower gross margin due to the high costs of production and distribution and marketplace businesses often have a lower gross margin because they typically take a percentage of each transaction as a fee, which reduces the overall profit margin of the business. Overall, the predictable and recurring revenue stream, low customer acquisition costs, and high gross margin of SaaS businesses can make them attractive to investors and contribute to higher valuations.

The results show that patents seem to increase a startup's valuation with a 10% significance level. The coefficient of 0.313 means that companies with registered patents get, on average, an increase of 37% in their pre-money valuations. Patents can provide the startup with a competitive advantage. By securing a patent for a new product or technology, the startup can prevent other companies from using it without its permission. This can give the startup a monopoly in the market, which can increase its value. Also, patents can be a form of intellectual property, which can be very valuable to investors. Holding a patent can demonstrate that the startup has developed something unique and valuable, making it more attractive to investors. Additionally, patents can provide the startup with revenue through licensing fees. If other companies want to use the patented product or technology, they may need to pay the startup a fee for the right to do so. This can provide the startup with a stable source of income, which can increase its value.

It is difficult to say whether fintech companies have historically received higher valuations than other startups, as valuations can vary greatly depending on several factors. In general, fintech companies that can demonstrate strong growth and profitability are likely to receive higher valuations than those that are not. Additionally, companies operating in the fintech space may be seen as more attractive to investors because of the potential for significant returns, given the increasing importance of financial technology in the global economy. From the regression results, there seems to be an indication that if the startup is a fintech, its pre-money valuation will, on average, increase; however, since the coefficient is not statistically significant, no conclusion can be withdrawn; also, in this sample, the majority of the unicorns[7] included are not Fintechs, which may also lead to skewed results.

Surprisingly, having heavy investment in R&D can, on average, decrease the startups' valuations. However, this conclusion fails to be significant. According to Miloud et al. (2012), investment in R&D should have a positive impact on a startup's valuation. However, that is different from what is gathered from these sample results. This incoherence can derive from the fact that to obtain this variable, two datasets had to be matched, thus, perhaps not contemplating all startups with investment in R&D. Nevertheless, one can reflect on the reasoning behind why the investment in R&D could influence the company's valuation negatively. If R&D investment consumes a significant portion of the company's resources without resulting in any revenue-generating products or services, for example. This can be especially damaging for early-stage startups with limited resources and the need to manage their expenses to achieve profitability carefully. Another way will be if it delays the company's product development timeline. This can cause the startup to miss important market opportunities and lead to decreased demand for its products or services, making it difficult for the company to generate significant revenue in the short term, reducing the company's valuation. Finally, R&D investment can negatively impact a startup's valuation if it is not aligned with the company's overall business strategy. If the startup is focused on developing products or services that are not in demand or that do not fit with the company's target market, the investment in R&D may not produce a sufficient return on investment - making investors hesitant, as they may perceive the risk is too high - and could ultimately decrease the valuation of the company.

It is important to note that the opposite outcome in the analysis of patents and R&D may be because the data used in the study was taken from two databases that were matched. In this case, not all companies in the database had both a patent and a high investment in R&D. This could lead to an inaccurate or misleading result in the regression analysis.

[7] A unicorn startup is a privately-held technology company with a valuation of $1 billion or more.

4.3. Founder effects

When inferring the founder’s effects on the pre-money valuation of a startup, three hypotheses were made regarding the founder’s previous startup experience (H7), its gender (H8) and whether or not the founder(s) attended a top university (H9). Surprisingly enough, the results from the sample seem to suggest that if the founder has previous startup experience, it will, on average, lead to a decrease in the company valuation. However, since the coefficient is not statistically significant, no conclusion can be drawn. A founder's experience can impact the valuation of a startup in both positive and negative ways. On the one hand, a founder with much experience in the industry in which the startup operates can bring valuable knowledge, connections, and expertise to the company. This can make the startup more attractive to investors and potentially lead to a higher valuation. On the other hand, a founder with too much experience in the industry may be seen as too conservative and unwilling to take risks necessary for a startup to succeed. These founders usually come from the corporate world and demand higher salaries. These can make investors less interested in the company, resulting in a lower valuation. Additionally, if a founder has a track record of failure, this can also negatively impact the startup's valuation. Ultimately, the impact of a founder's experience on the valuation of a startup will depend on the specific details of the situation.

When the founder is a female, the results show that the startup’s valuation will, on average, increase. If a startup's founder is a female, this may be seen as a positive signal to potential investors, as it indicates a level of diversity and inclusivity within the company. Additionally, research has shown that companies with diverse leadership tend to perform better financially, so investors may see a female founder as a potentially good investment. On top of these, LPs can also pressure their VCs to have a more comprehensive portfolio in terms of inclusivity, making investing in female-founded businesses even more attractive.

Finally, when the founder attends a top university, it positively impacts, on average, the valuation of its startup by 36%, given the 0.308 coefficient with a confidence level of 1%. The impact of a founder's education on a startup's valuation can vary depending on several factors. In general, investors may see a founder who has attended a top university as having had access to a high-quality education and a strong network of potential mentors, collaborators, and investors. As a result, they may view this founder as having a more significant potential for success and may be more willing to invest in the startup. Additionally, attending a top university can also provide a founder with valuable skills and knowledge that can be applied to their business, which can help the startup to grow and succeed.

4.4. Sub-sample analysis

To understand if there was any skewness of the results due to the atypical periods contained in the sample – in this case, the Portuguese financial crisis and the COVID-19 pandemic - the same methodology was applied to a sub-sample, excluding all companies launched in 2009, 2010, 2011, 2012, 2013, 2019 and 2020.

All the statistical tests mentioned in section "3.3. Model estimation and descriptive statistics", performed on the full sample, were also applied to this sub-sample analysis. The results of the regression are as follows:

Table 4. *Models 1, 2, 3 and 4 for the log of pre-money valuation regression*

A sub-sample of 118 companies - derived from the original sample - was used for these regressions. The log of the pre-money valuation is the dependent variable (calculated by subtracting the amount invested in the last financing round to the post-money valuation of the company). Entries are the coefficients and, in parenthesis, the t-statistics. The test performed is a two-tailed test statistic, which is computed for 90%, 95% and 99% confidence levels. One, two, or three asterisks refer to significance at 10%, 5%, and 1%, respectively.

		(1)	(2)	(3)	(4)
		Control Variables Only	Control Variables + Startup Characteristics	Control Variables + Founder Effects	All variables
Variables Name	Stata Variables Name	Model 1	Model 2	Model 3	Model 4
Log of Nasdaq Composite Index	log_ixic	0.341	0.335	0.208	0.216
		(0.306)	(0.313)	(0.309)	(0.319)
Firm Age	age	**0.00395****	**0.00406****	**0.00380****	**0.00414****
		(0.00166)	(0.00169)	(0.00165)	(0.00173)
Development Stage	stage	**0.579*****	**0.546*****	**0.529*****	**0.481*****
		(0.0933)	(0.101)	(0.0953)	(0.104)
Acquisition Status	status	0.105	0.0730	-0.0552	-0.0892
		(0.227)	(0.235)	(0.245)	(0.253)
Number of Employees	size	**7.01e-05*****	**6.01e-05****	**7.47e-05*****	**6.36e-05****
		(2.27e-05)	(2.53e-05)	(2.28e-05)	(2.54e-05)
Client Focus	focus		0.0395		0.0620
			(0.0802)		(0.0816)

Headquarters' Location	hq		-0.287		-0.323
			(0.295)		(0.292)
Business Model	bus_model		0.0809		0.106
			(0.0865)		(0.0896)
Intellectual Property	patent		0.0446		0.149
			(0.230)		(0.232)
Fintech	fintech		-0.0482		0.0213
			(0.226)		(0.227)
Research and Development	rd				-0.0781
					(0.243)
Prior Startup Experience	experience			0.00628	0.0263
				(0.123)	(0.127)
Founder Gender	gender			0.171	0.250
				(0.161)	(0.173)
Founder Attended Top University	top_uni			**0.280***	**0.310****
				(0.142)	(0.150)
	Constant	-0.116	-0.133	-0.119	0.0868
		(0.390)	(0.487)	(0.389)	(0.488)
	Observations	118	118	118	118
	R-squared	0.445	0.454	0.469	0.485

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

From the regression outputs, the previously statistically significant variables lost some or all their significance in this sub-analysis. In addition, some coefficients also changed signals to reflect the influence of the atypical periods covered in the first regression (Table 3).

In the full sample, it has been found that startups whose client focus is B2B companies positively impact valuations. However, the coefficient indicates that this trend does not hold for the regression in Table 4. Instead, it appears that B2B companies tend to perform well, especially during times of high uncertainty. There are several possible explanations for this phenomenon. Firstly, B2B companies often have long-term contracts or agreements with their customers, providing a degree of stability in terms of demand for their products or services. This can be particularly valuable during a crisis when demand may be uncertain. Secondly, B2B companies may be able to leverage their position as a supplier to negotiate better terms with their customers during a crisis. For example, they may be able to secure longer payment terms or lower prices in exchange for maintaining or increasing their level of business, which can help to reduce costs and improve profitability. Finally, B2B companies may be more specialized and focused on serving specific industries or markets, making them more resilient to changes in demand or economic conditions.

It is worth noting that, while not statistically significant anymore, the results suggest that companies with headquarters in Portugal may have a negative impact on their valuations, as previously seen in the first regression. Additionally, there is a conflicting outcome concerning the impact of business model on a company's valuation. When excluding the crisis periods, it appears that SaaS companies perform better when atypical periods are also considered. This outcome could be attributed to several factors. Firstly, SaaS companies typically have a subscription-based business model, which generates recurring revenue from customers, providing stability and predictability in their revenue streams. Secondly, SaaS companies often offer flexible pricing options, such as pay-as-you-go or usage-based pricing, which can make their products and services more attractive to customers during a crisis when budgets may be tight. Thirdly, SaaS solutions can help companies reduce IT costs by eliminating the need for upfront investments in hardware and software, as well as ongoing maintenance and support costs. Fourthly, SaaS solutions can be accessed and used remotely, which can be particularly useful during a crisis when employees may be required to work from home. Finally, many SaaS solutions provide essential services, such as communication and collaboration tools, which may be in high demand during a crisis when companies are looking to maintain productivity and connectivity.

The sub-sample analysis found that Intellectual Property loses significance when considering more challenging periods, as having that competitive advantage can be particularly important in such circumstances. On the other hand, Prior Startup Experience appears to gain greater importance when excluding atypical periods. This may be because, even with a great deal of experience, it is difficult to thrive during a crisis. While a startup with a founder with prior experience may be better equipped to navigate a financial or economic crisis than one without such knowledge, it is not a guarantee of success. The company's business model, product, or market may be particularly vulnerable to the impacts of the crisis, regardless of the founder's experience. The situation may be of such a magnitude and severity that even experienced founders and businesses struggle to survive. Lastly, Founder Attended Top University is relevant in both the full sample and sub-sample, indicating that this is always a good criterion when evaluating an investment opportunity.

The remaining variables, i.e., Fintech, R&D and Founder Gender, did not significantly change compared to the outcome already studied in the full sample analysis.

This analysis worked as a robustness check, which is very important when working with regression analysis, to help ensure that the analysis results are reliable and not influenced by outliers or other anomalous data points.

5. Conclusion

In conclusion, this research aimed to investigate how firm characteristics - past literature found to be relevant but also new ones I added - affect the valuation of a Portuguese startup. These characteristics were all included in a model to help predict, always combined with other valuation methods, the pre-money valuation of a startup.

Despite their industry or stage focus, all VCs can use this model to support their decision process when scouting new opportunities. The outcome of this study could even be used, for example, to automatise the decision-making process of a VC using AI, which would leave more time for these investors to focus on their portfolio companies.

In this research, a 4-model approach was used. The control variables, such as the Nasdaq Composite Index, Firm Age, and Development Stage, had a slightly positive but non-significant impact on the Pre-Money Valuation. In addition, the Acquisition Status had a negative but non-significant impact, and Number of Employees had a negative and statistically significant effect.

The research was divided into nine hypotheses, one for each criterion considered in the study, and separated into two different categories. The factors contributing to increased valuations are startups with a B2B focus, HQ outside of Portugal, a SaaS business model, registered patents, and fintech-focused. A startup does not necessarily have to invest heavily in R&D to be perceived by investors as a better opportunity. Another important finding is that a founder having prior startup experience is not necessarily an indicator of higher valuations. Companies with female founders or founders attending a top university also have higher valuations. The limitations of this empirical study should be considered when interpreting the results. The study was subject to various sources of bias, both from the assumptions of the original dataset and my own while cleaning the data. This may have impacted the accuracy of the results and the conclusions drawn. Also, the cost and time required to conduct this study may have limited its scope and availability to gather more relevant data. This may have introduced additional sources of bias and reduced the sample's representativeness.

Overall, a smaller sample size in statistical analysis can lead to lower precision of estimates, higher variance in estimates, an increased likelihood of overfitting, and an increased risk of bias in the estimates. This can make it difficult to draw reliable conclusions and accurate predictions using the model. Hence why it is understandable why the final model does not yield many statistically significant results, which could indicate that the observed relationship between two variables could not be real or simply a result of random chance. It is important to note, however, that statistical significance does not necessarily imply practical or real-world significance. While statistical significance is an essential criterion for determining the reliability of a statistical relationship, it does not necessarily reflect the importance or magnitude of the relationship in the real world. For example, a statistical relationship may be statistically significant but have a small effect size and, therefore, may not be practically significant. On the other hand, a relationship may not be statistically significant but still have a large effect size and be important in the real world. When interpreting statistical analysis results, it is crucial to consider both statistical and real-world significance. Real-world significance is often more relevant to decision-making and can help determine a statistical relationship's practical implications.

The results of this study provide valuable insights into the factors that influence the valuations of Portuguese startups. The central database used is highly credible, and the fact that various sources of information (Dealroom, Refinitiv Eikon, and List of entities recognized in the practice of Research and Development activities) were combined into the final dataset makes it unique and valuable for the VC community. In addition, although not massive, the sample is comprehensive and similar in size to the one used by Miloud et al. (2012), the study that served as inspiration for this dissertation.

These findings can be helpful for investors and entrepreneurs when assessing the value of a startup, as well as for policymakers and stakeholders interested in supporting the growth and success of startups in Portugal.

To fully understand this topic, future research needs to address the limitations of this study and build upon the findings presented here. This will help to deepen the understanding and provide a more comprehensive view of the subject. With continued research and exploration, it is possible to continue advancing knowledge in this area and improve the ability of VCs to value new investment opportunities properly. Future research in this area could consider other variables, for example, the volume of financing rounds in VC over the months of the year, to then try to explain the volatility in the valuations; and countries, as well as how these variables interact with one another in influencing valuations. It would also be advantageous to merge other datasets to obtain an even more complete and larger sample and more robustness checks using different sample periods.

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7. Appendix

Appendix A: Graphical representations of the primary sample (2000-2022)

To better understand the sample used for this dissertation, some graphical representations of its most essential aspects are below.

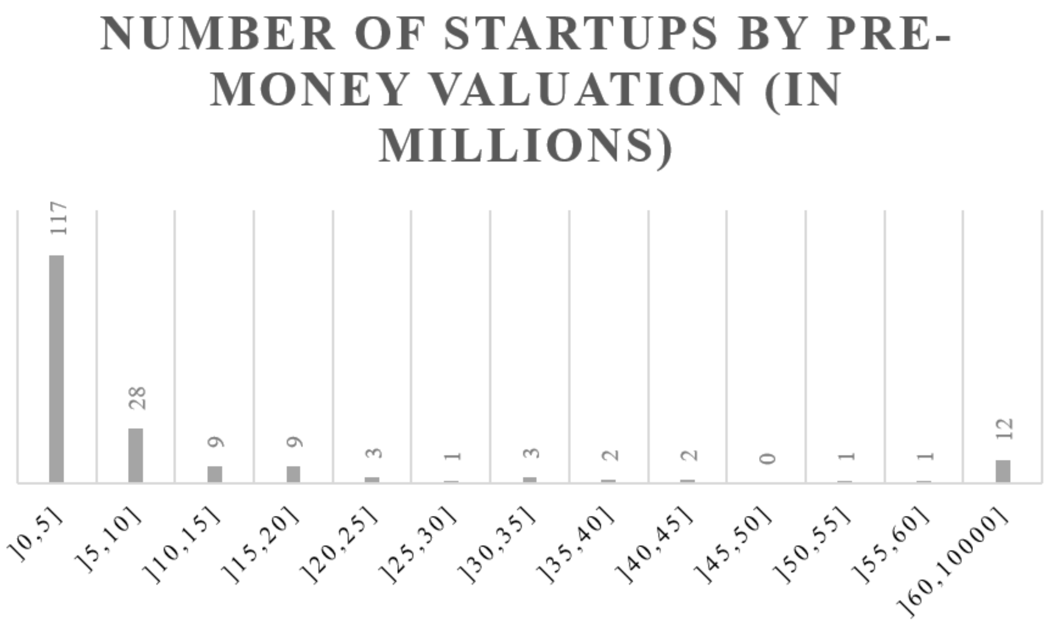

Figure 1. *Number of startups by pre-money valuation (in millions)*

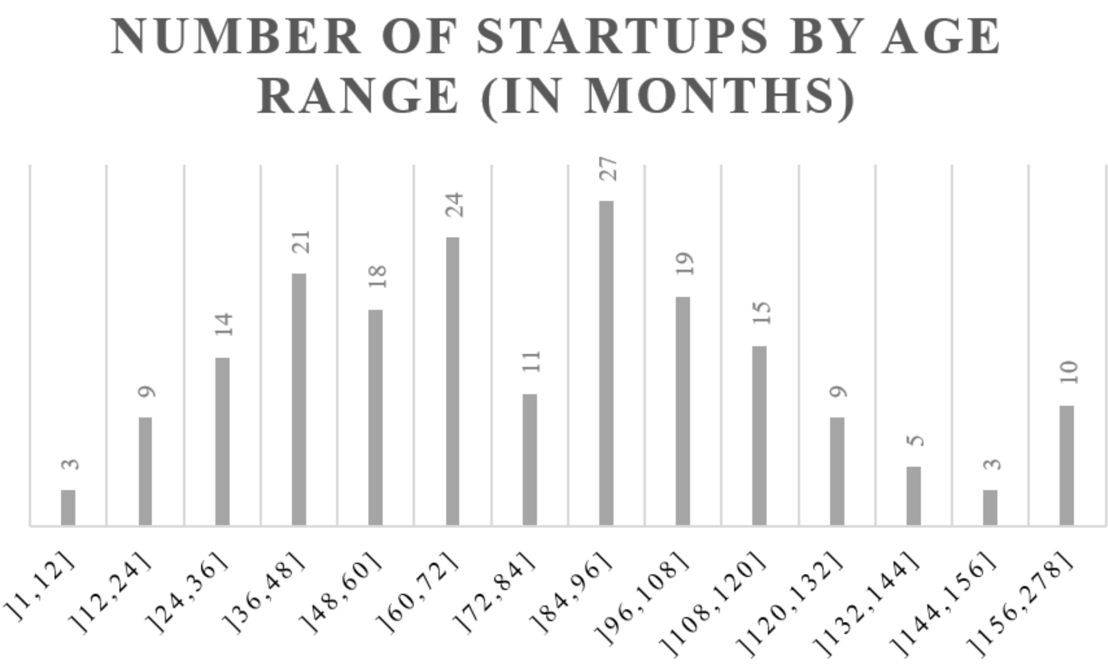

Figure 2. *Number of startups by age range (in months)*

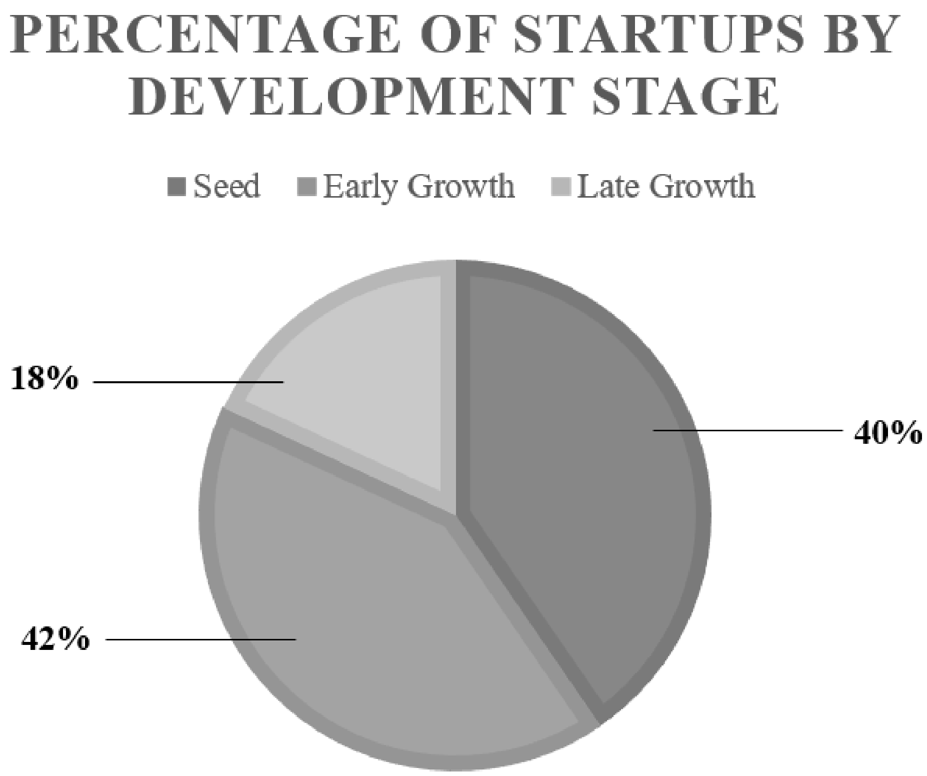

__Figure 3.__ Percentage of startups by development stage

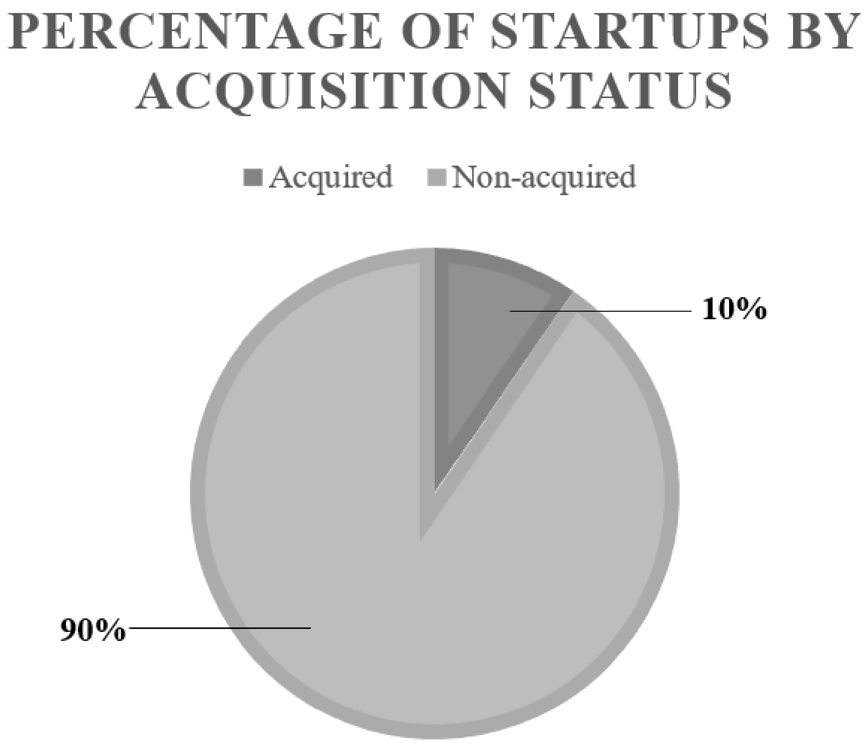

__Figure 4.__ Percentage of startups by acquisition status

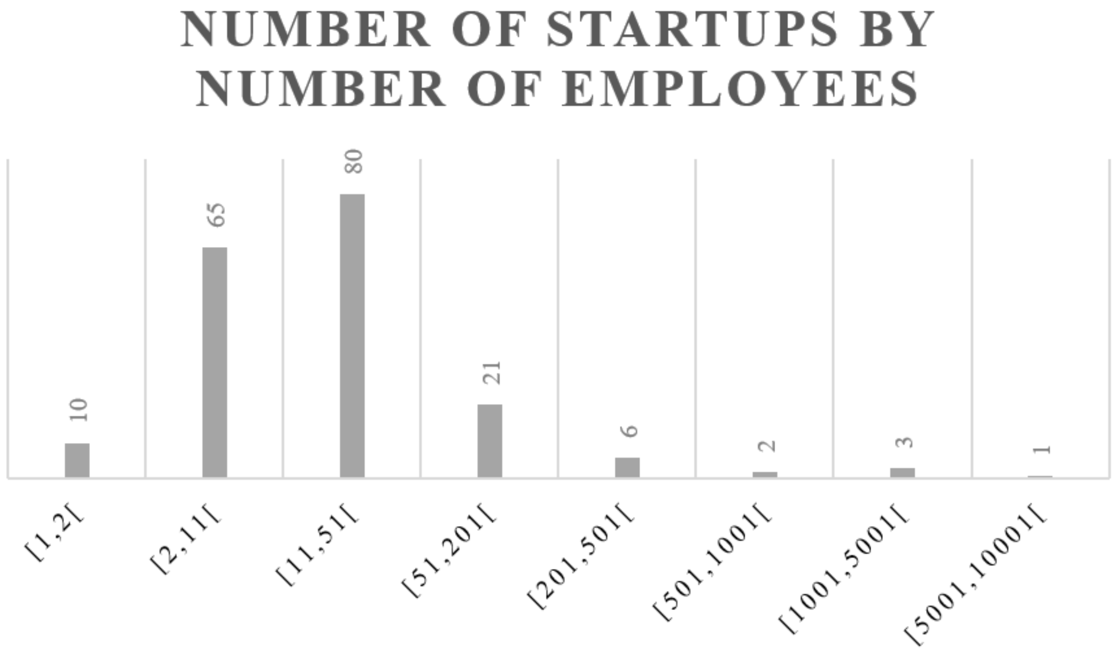

Figure 5. *Number of startups by number of employees*

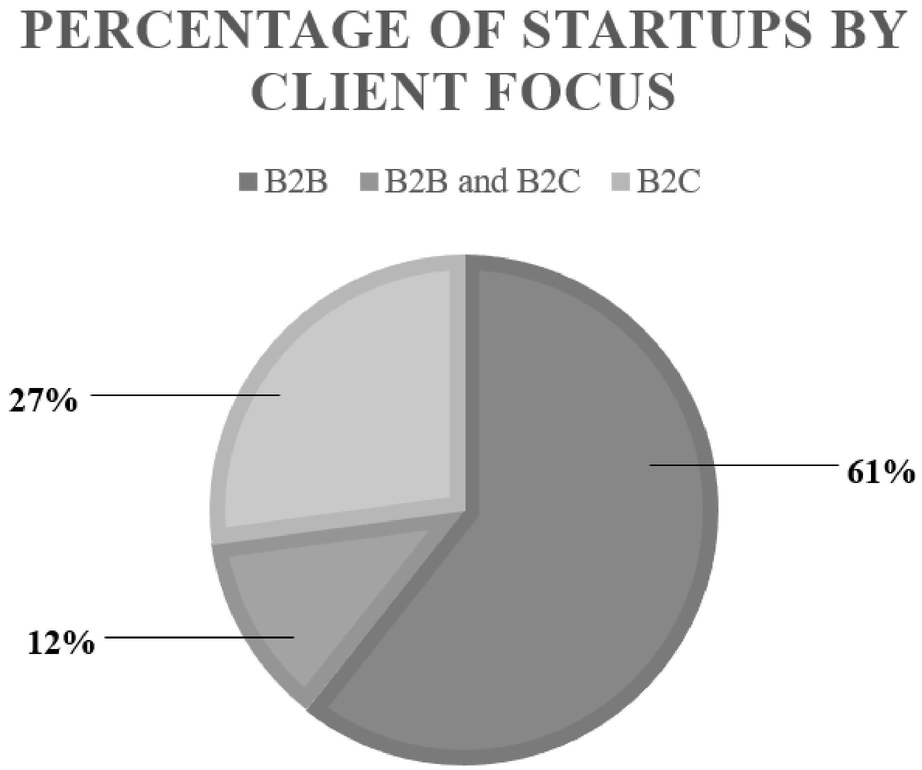

Figure 6. *Percentage of startups by client focus*

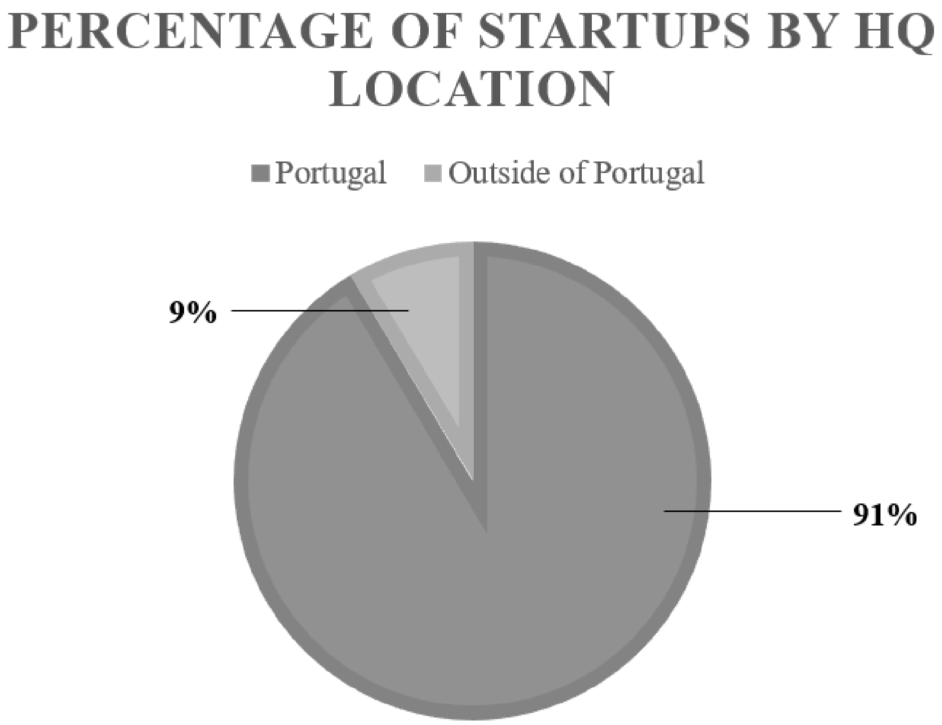

Figure 7. Percentage of startups by HQ location

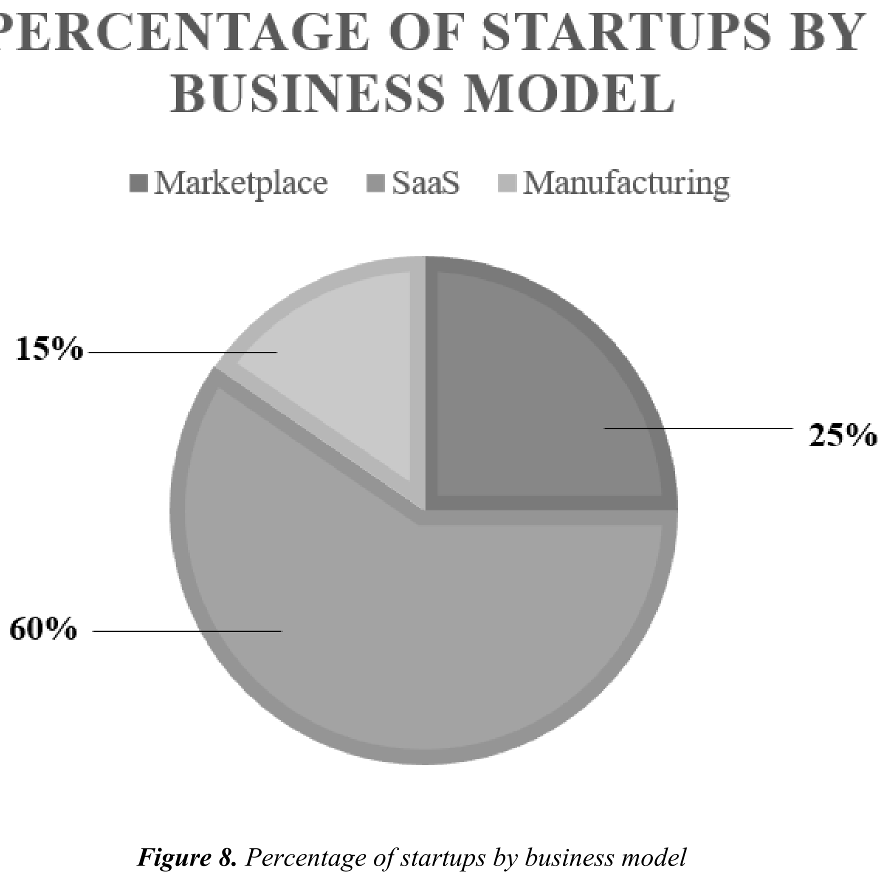

Figure 8. Percentage of startups by business model

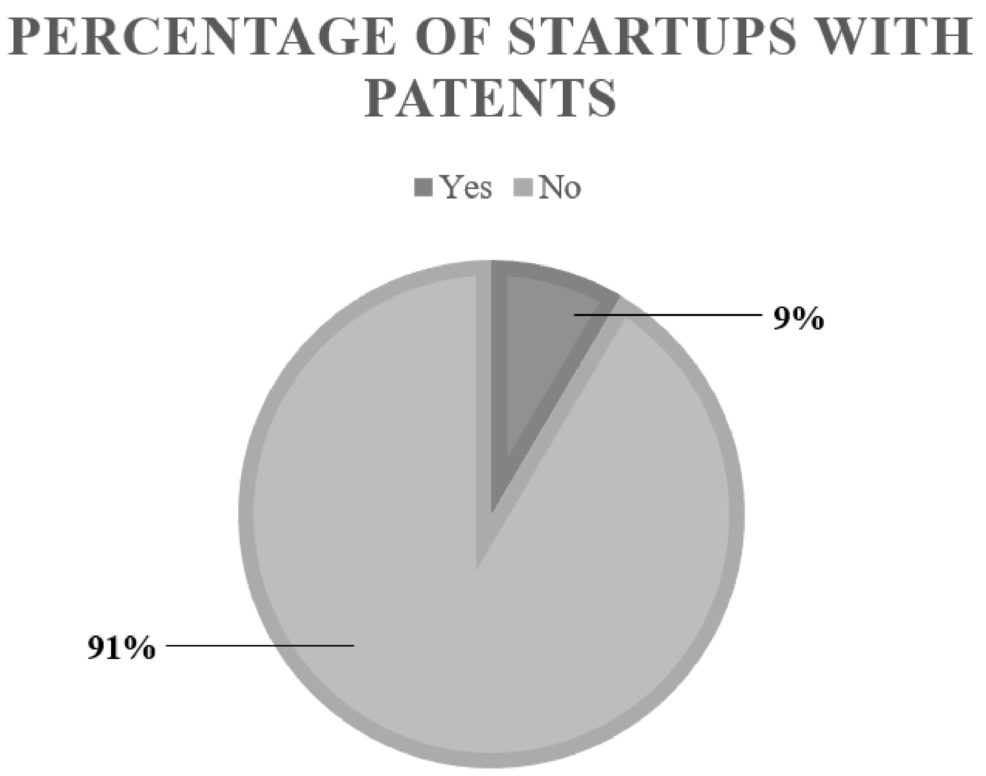

Figure 9. Percentage of startups with patents

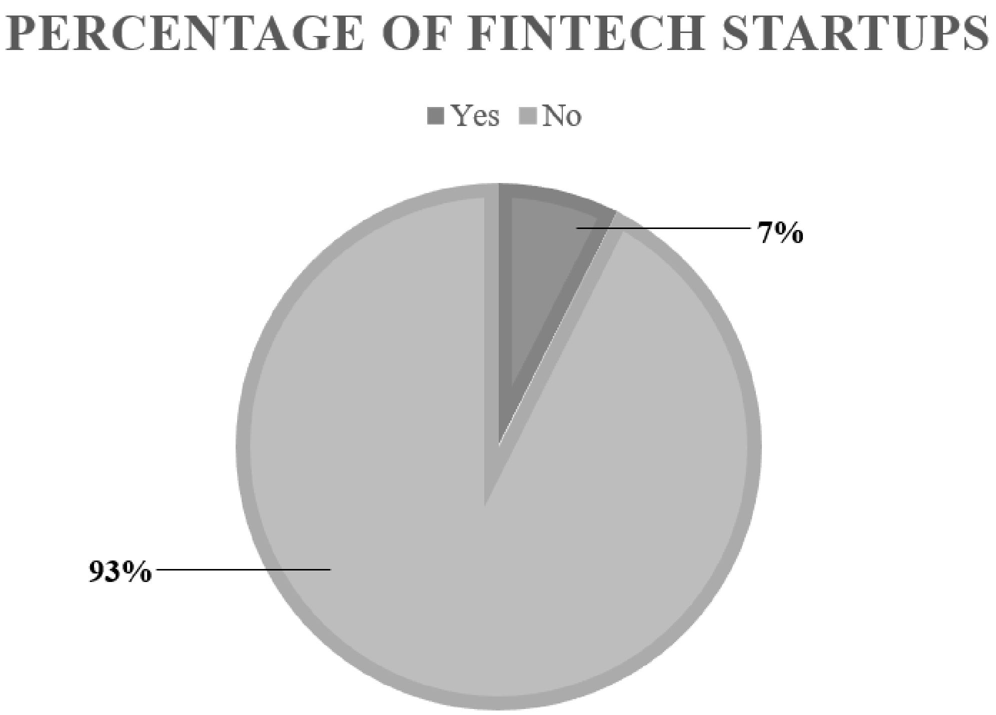

Figure 10. Percentage of fintech startups

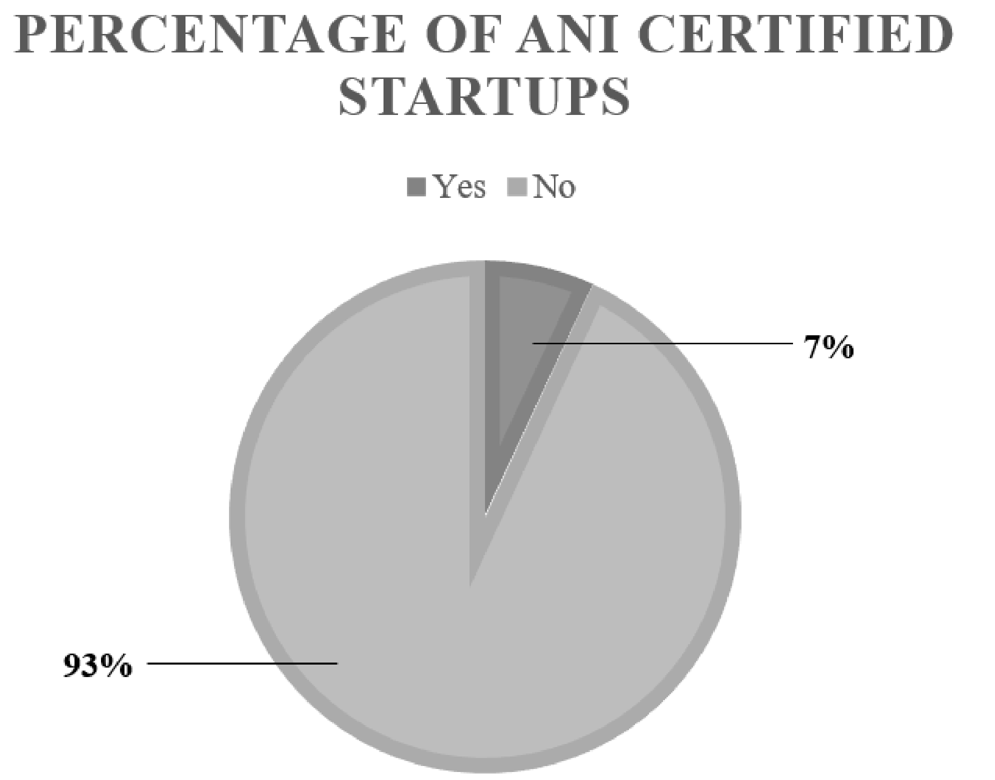

Figure 11. Percentage of ANI certified startups

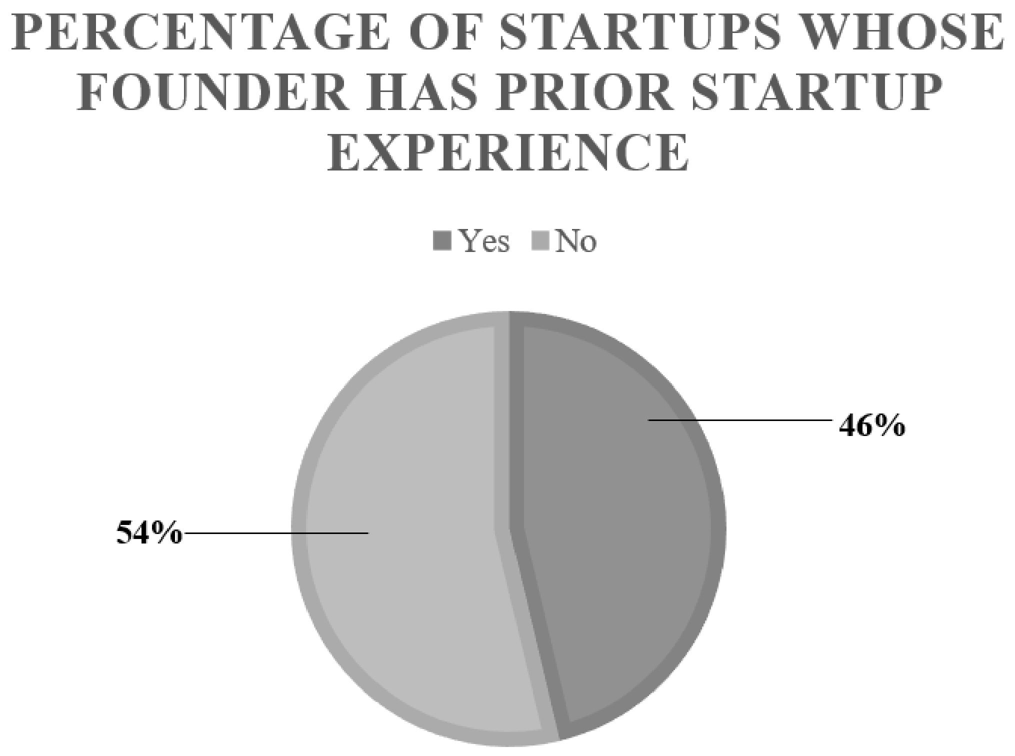

Figure 12. *Percentage of startups whose founder has prior startup experience*

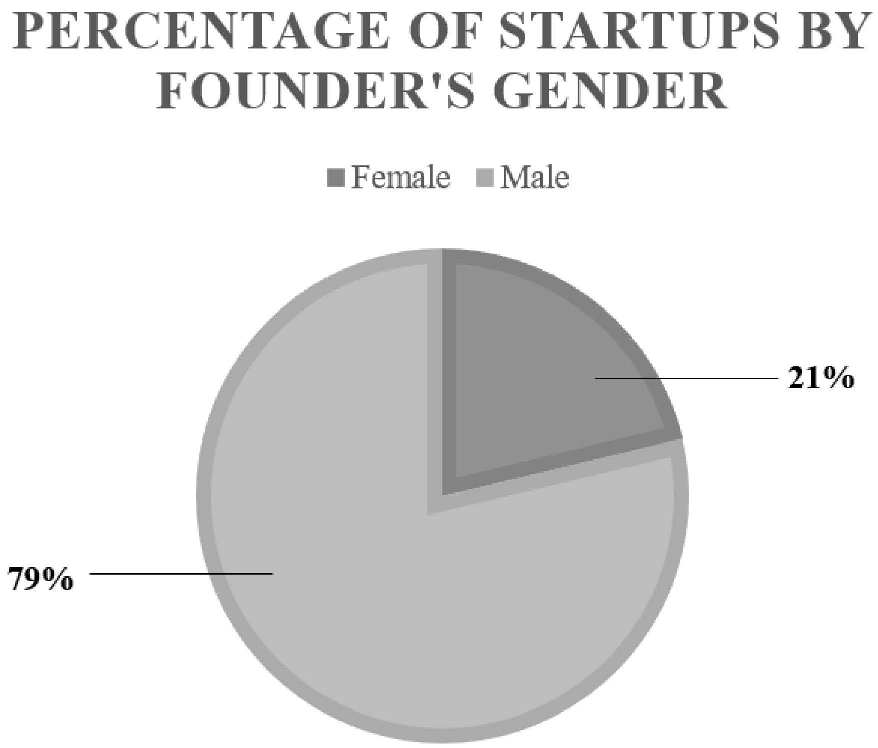

Figure 13. *Percentage of startups by founder's gender*

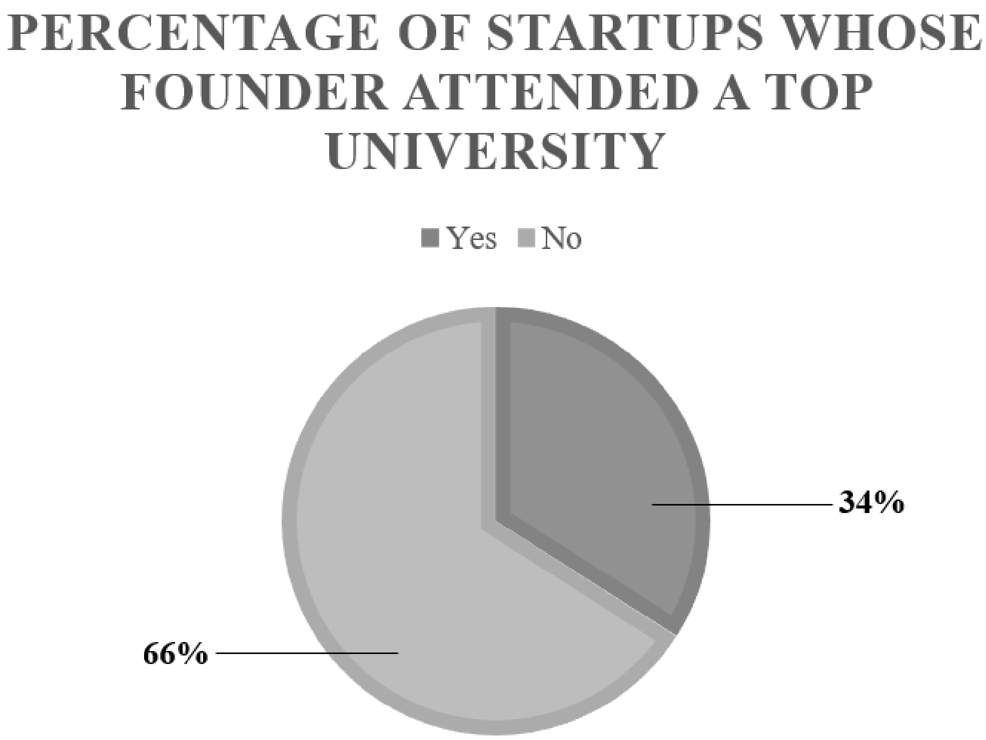

Figure 14. *Percentage of startups whose founder attended a top university*

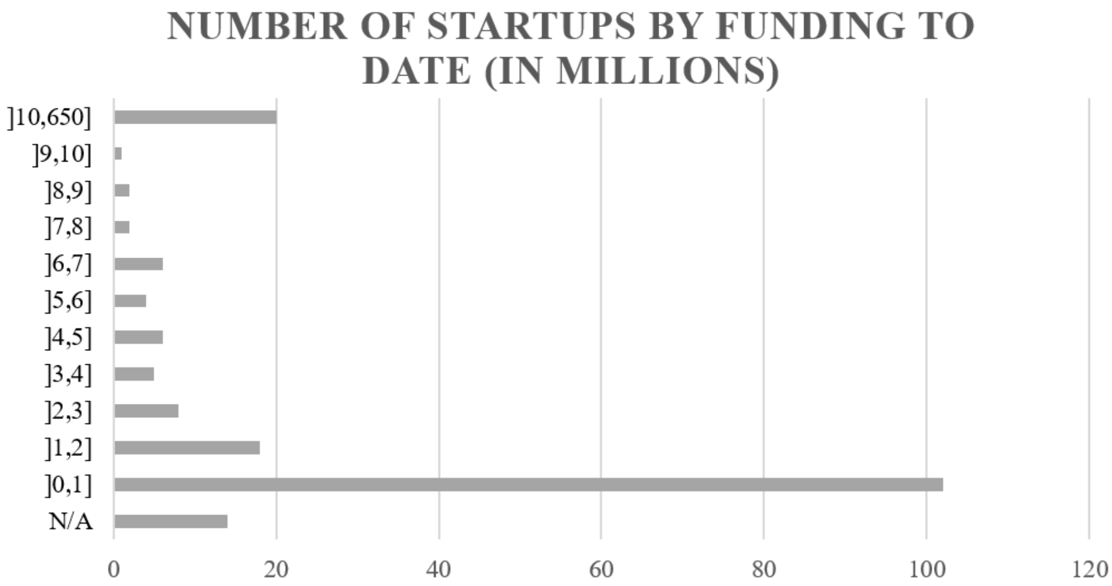

Figure 15. *Number of startups by funding to date (in millions)*

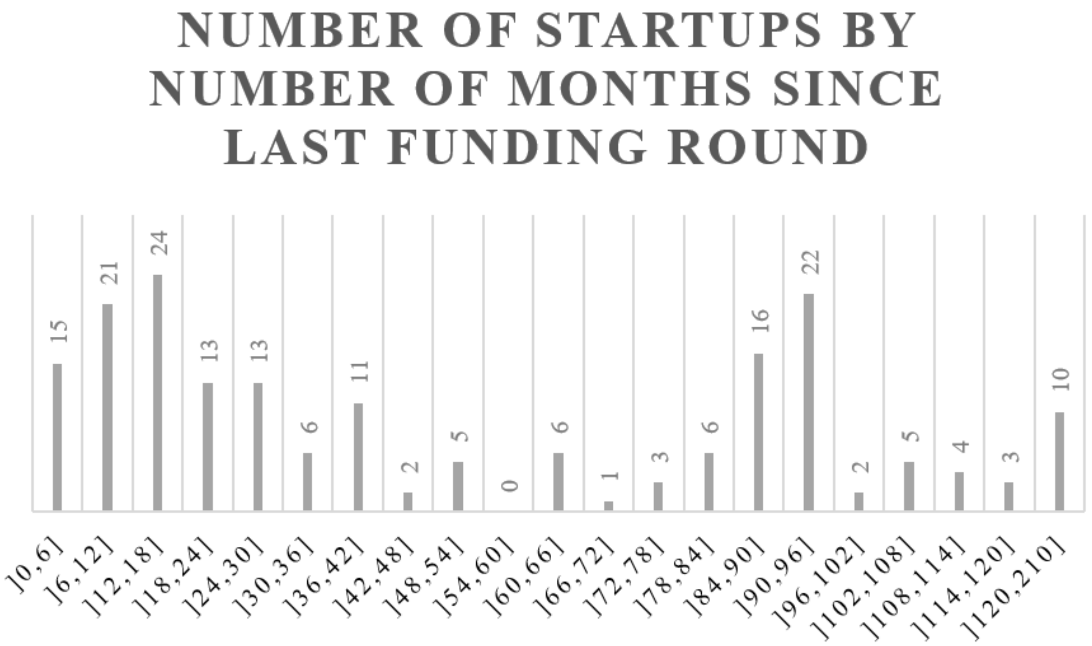

Figure 16. *Number of startups by number of months since last funding round*

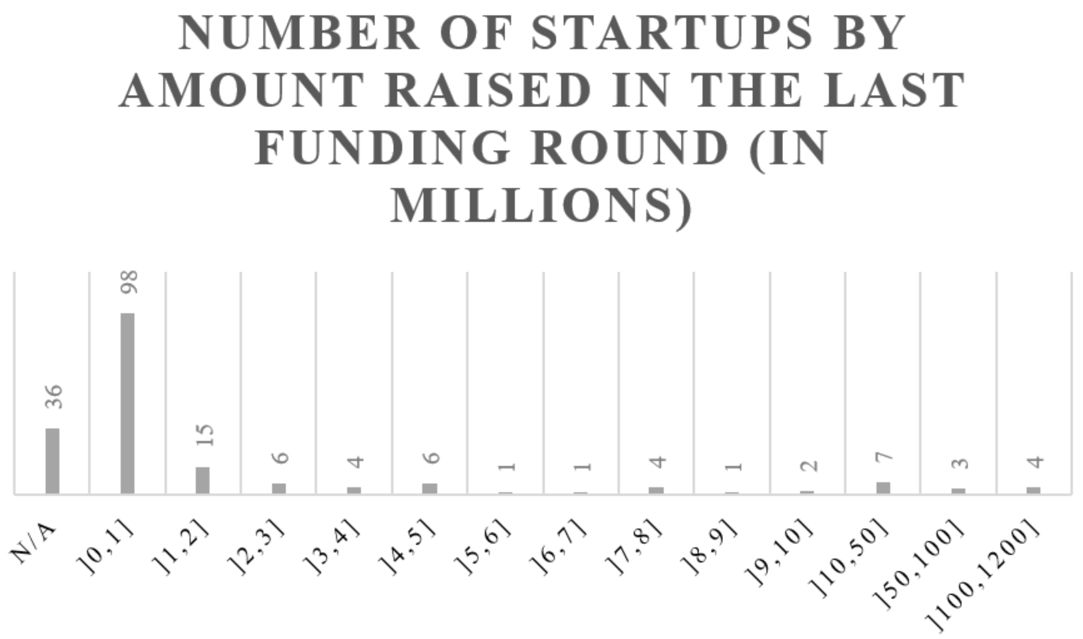

Figure 17. *Number of startups by amount raised in the last funding round (in millions)*

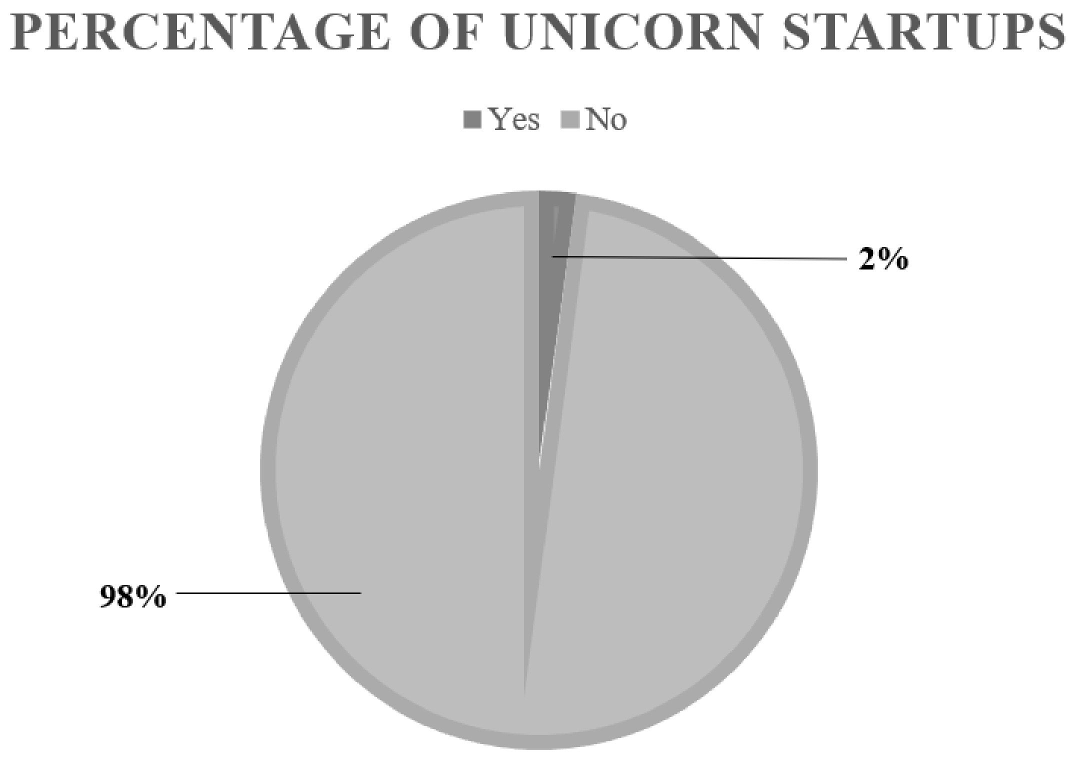

Figure 18. *Percentage of unicorn startups*

Appendix B: Table 5 – Correlation Matrix

The correlation coefficients for each explanatory variable are displayed in the matrix below. The matrix's diagonal is 1 since it represents the correlation between a variable and itself.

Table 5. *Correlation matrix*

VARIABLES	(1) log_premoney	(2) log_ixic	(3) age	(4) stage	(5) status	(6) size	(7) focus	(8) hq	(9) bus_model	(10) patent	(11) fintech	(12) rd	(13) experience	(14) gender	(15) top_uni
(1) log_premoney	1.0000														
(2) log_ixic	0.0069	1.0000													
(3) age	**0.2345***	**-0.6926***	1.0000												
(4) stage	**0.6274***	0.0109	**0.2316***	1.0000											
(5) status	0.0544	**-0.2327***	**0.1529***	0.0252	1.0000										
(6) size	**0.3155***	-0.0832	**0.1888***	**0.1828***	-0.0316	1.0000									
(7) focus	**-0.1618***	0.0033	-0.0827	**-0.1585***	0.0007	0.0886	1.0000								
(8) hq	**-0.4012***	0.0627	**-0.1686***	**-0.2755***	-0.0951	**-0.3204***	0.0793	1.0000							
(9) bus_model	0.1119	0.0761	-0.0264	**0.2005***	0.0498	-0.0188	**-0.2463***	-0.0240	1.0000						
(10) patent	**0.1578***	-0.1076	0.0940	0.0671	-0.0992	0.0287	**-0.1446***	**-0.1802***	**-0.1551***	1.0000					
(11) fintech	0.1196	0.0548	-0.0472	0.1143	-0.0923	0.0060	-0.0535	-0.0587	0.1311	0.0587	1.0000				
(12) rd	0.0638	0.0529	0.1359	0.0832	-0.0887	0.0093	-0.1352	-0.0671	-0.0771	0.0671	-0.0773	1.0000			
(13) experience	0.0934	-0.0473	0.1295	0.1230	0.0243	0.0909	-0.0835	-0.0992	0.0371	-0.0155	0.0212	-0.0007	1.0000		
(14) gender	0.0364	0.1050	-0.0861	0.0344	0.0075	-0.0260	-0.0237	**-0.1675***	-0.0987	0.0277	**-0.1475***	**0.1657***	-0.0654	1.0000	
(15) top_uni	**0.2693***	0.0452	0.0617	**0.2014***	**0.1903***	-0.0284	-0.0887	**-0.1469***	0.0633	-0.0550	-0.0297	**0.1618***	**0.1999***	-0.0387	1.0000

*** p<0.01, ** p<0.05, * p<0.1