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Factors Affecting Successful Capital Raising for Startups: Evidence from the US Capital Market

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Abstract

Aim: This article aimed to analyse the selected factors that have an impact on the success of acquiring capital of a startup company on the capital market. The discussed research question was: Does information, such as the founder's background, education, experience, and amount of funding acquired previously, have a positive impact on the amount of capital that will be acquired in the next rounds of funding?

Methodology: An econometric analysis was performed on the effect of the entrepreneur's experience and background on the success of the next rounds of funding, using an OLS linear regression model. The study used selected factors that analysed data on the US market.

Results: The model's joint statistical significance suggests that the explanatory variables have an effect on the explained variable.

Implications and recommendations: The results may be important for new startup companies requiring external financing from capital markets. The study focused on the initial financing situation of startups based on data from the USA.

Originality/value: The main value of the research was the identification of factors showing low significance (type of profession: consultant, teacher, Google or Microsoft employee) and those significant (e.g. profession of director).

Keywords: startup, capital markets, venture capital

1. Introduction

Most academic articles on start-up financing analyse the topic from the perspective of investment risk and focus on the benefits to the investor, which overlooks the venture capital investment process and the fact that this area of economic activity should improve its performance − generating more reliable returns for the investor. In order to improve, the owners must know what factors are important to obtain external financing for their just-started but still immature project. This research gap is the focus of the paper, important from both an academic and practical point of view.

Startups as young companies are under significant pressure to quickly commercialise their product. With low capital and experience, startups may not qualify for institutional capital investment at the beginning, therefore it is important for startups to raise funding for short and long-term growth during the establishment phase (Janaji et al., 2021).

This study is important for many reasons, the main one being the need to provide startups with additional interest as they are the essence of innovation leading to the most anticipated type of economic growth. Hence, supporting investment in high-risk companies is necessary for the economy to enter a higher level of development through investing in innovation.

A startup can be defined as a company created by an entrepreneur, or group thereof, to design and develop an innovative and scalable product; however, they are not merely any new entrepreneurial project but have a clear goal of the rapid introduction of their creation with the intent of global distribution. A frequently used term is the startup ecosystem, which refers to the interconnected network of resources, people, organisations and institutions that support the creation, development and success of start-ups (Huggins & Thompson.2021).

The research objective was to analyse the determinants of success to acquiring additional funds on capital markets by startup companies, and in particular to verify if the factors selected by the authors have a positive impact on the success in capital acquiring by startups on the capital market. The study used data on the US market, with the dataset acquired from Kaggle.com.

Taking into account the rapid growth of startup and their needs for external financing for the rapid pace of development, the authors formulated the following research hypothesis: *information, such as the founder's background, education, experience, and amount of funding acquired previously, has a positive impact on the amount of capital that will be acquired in the next rounds of funding*. To verify this hypothesis, the ordinary least squares method was employed in order to estimate a linear regression model. The dataset, created in 2019, contained two tables with data about startups created between the years 2000 and 2019 (the first – 1206 companies, and the second – 573 entries of detailed information about the founders, referenced in the former). After joining these tables, 453 usable observations were left, with each observation containing the whole set of variables from the two initial ones, which contained many new recently created startup companies, but also some established and well-known companies, e.g. YouTube, WhatsApp, Instagram and others.

The next section presents the basic concepts about capital markets and figures for the US market, along with an overview of the financial life cycle of a typical startup. Section 3 provides a literature review, and Section 4 describes the research methodology including an econometric part where the OLS model was performed. The dataset was created by merging two tables, one containing the startup data, and the second – the founders' data. This allowed to associate each startup to their respective founder and analyse the data as a single set. Section 5 presents the research results, where the descriptive statistics were calculated and analysed. Scatterplots were used to better understand the relationships between variables. Thus, the model was estimated and verified as jointly statistically significant. The individual variables were also examined against statistical significance, and the model was tested with a variety of diagnostic tests. Finally, the regression results were presented and interpreted in the context of the model, and the interpreted information was used to verify the research hypothesis. The main conclusions and discussion were outlined.

2. The Capital Market, the Financial Life Cycle of a Startup Company

The capital market is known as a place where new financial securities are created and sold. Most notably, debt (in the form of bonds) and equity (stocks) can be issued. Bonds can be generally classified depending on the credit rating as investment-grade bonds and non-investment grade (or junk bonds). Investment-grade bonds are issued by corporations with very strong capacity to repay them. Non--investment grade bonds are associated with a high risk of default – the debtor not being able to pay back the principal and interest, which is why they are often called junk bonds or speculative bonds. Following the main topic of this paper, the basic concepts about capital markets and figures of US market are presented in this section.

An operating company can decide to issue more shares to raise capital for future investments. It can offer those shares for sale either privately – only to a select group of individuals or institutions – or publicly via an Initial Public Offering (IPO). However, according to Gutterman (2023), the widely held view that startups grow and sustain themselves through external funding is not true. In the US market in 2015, 60% of the fastest-growing startups were created through the use of 'bootstrapping' techniques with less than $10,000 in capital.

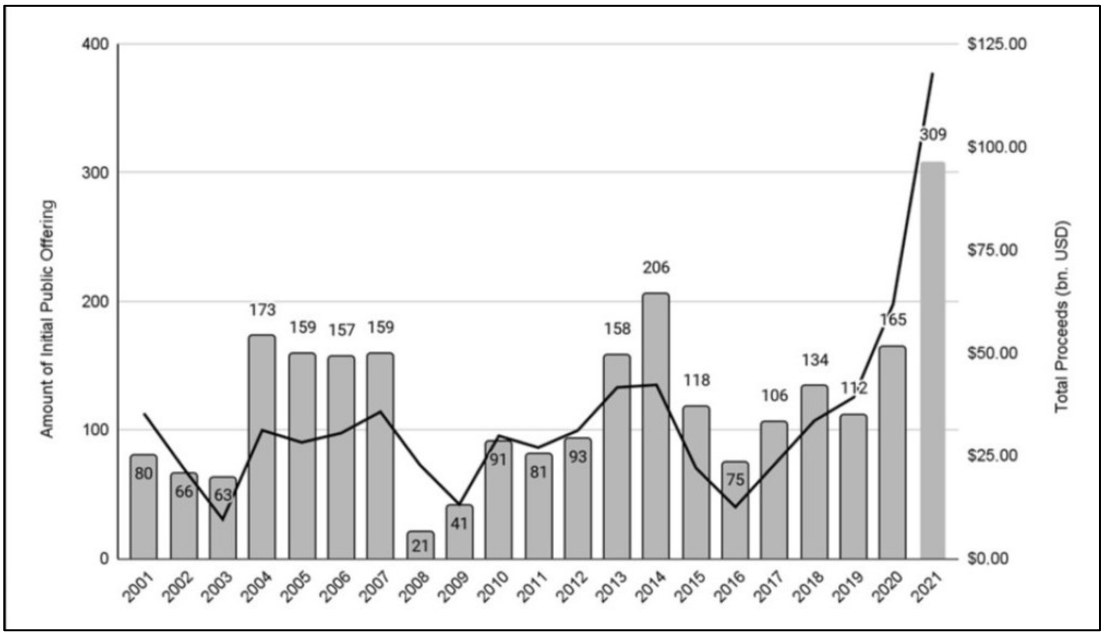

Fig. 1. Number of IPOs in the US and their revenues in 2001-2021

Source: authors' work based on: Ritter (2022).

In Figure 1 the number of IPOs made each year in the US can be seen as bars corresponding to the left vertical axis. The line graph corresponds to the right axis which shows total IPO proceeds from each year in billions of dollars; also note that the total capital raised each year was closely correlated with the amount of IPOs.

The optimal allocation of assets is one of the most important problems in economics. The role of the capital markets is primarily to allocate resources in the economy efficiently and at low transaction costs. Scholars also stress the importance of efficient capital markets in the economy. Bekaert & Harvey (1998) explained that efficiency, in this case, has multiple implications: efficient allocation of capital, and efficient prices. This means that efficient capital markets not only effectively allocate capital among agents in the economy, but also price the assets fairly. The researchers noted that to achieve the efficient pricing of assets, information must be available to all investors.

Financial intermediaries play a significant role in the financial system. These are institutions such as banks, hedge funds, venture capital funds, and others that provide financial services to companies and individuals. Demirguc-Kunt & Levine (1996) suggested that the aforementioned assumptions were false, and the opposite effect was observed. They also reported that financial institutions reduce information asymmetries, such as adverse selection problems, that can have a negative impact on market efficiency. Furthermore, Bekaert et al. (1995) stated that intermediaries impose a positive effect on capital markets through the aggregation of household savings and the allocation of those funds in the economy.

The financial life cycle of a typical startup begins with an idea. The company needs funds to start functioning, and while it is possible to fund such a company exclusively using the founders' own capital, the revenue generated in the beginning would be low and so the growth would be mediocre, which is why startups depend on outside capital. In order to facilitate the speed-of-lightning growth, huge amounts of capital are needed to invest in the product, marketing infrastructure, and most importantly, human capital. Most startup companies today revolve around technology, computer science, software, and other innovative concepts, hence assembling a team of talented and creative experts is essential to the success of the venture, as it is quite expensive to hire such a team and provide them with the necessary tools to create an innovative product.

The first formal capital raised, where the new company issues new equity in exchange for investors' capital, is called a series A round of investing, with subsequent rounds called B, C, and so on. At such an early stage it is very hard to estimate a valuation of a startup that has little or no revenue and the risk of failure is still very high, therefore the valuation is often limited to negotiations between the founders and the investors. The founders need to assess how much capital they need to raise to keep their business running until the next round (or profitability), and how much equity they are willing to give up. The investors, on the other hand, consider how much capital they want to risk and how much equity is fair in exchange for the investment, and also need to take into account the maturity of the business and the risk involved. The key negotiation aspect of each round is the pre-money and post--money valuation. The pre-money valuation is the price at which the investors agree to value the company before the new investment. Similarly, the post-money valuation is the valuation of the company after the investment has been made – this is essential because it translates into the size of the stake that the investor will receive. For example, a post-money valuation of $1 million and an investment of $100 thousand would mean that the investor is buying 10% of the company. Alternatively, a valuation of $2 million with the same investment would mean that the investor will buy only 5% of the business. Thus, the investors will be negotiating to drive the post-money valuation down, and conversely, the founders will argue for the valuation to be higher. The relationship between the aforementioned metrics can be described by the formula shown in Example 1.

Example 1. Relationship between the invested capital and the post-money valuation:

$$investor's\ stake = \frac{investment}{valuation},$$

where:
investment − the capital that is to be invested into the company,
valuation − the post-money valuation agreed by both parties.

From the point of view of the investors, the last part of the lifecycle of a startup is the exit, which is a way for investors to sell their shares in the company and realise the profits (or losses) from their investment in the startup. They can either sell their shares to another venture capital fund or private investor, or they can sell to the public by executing an Initial Public Offering (IPO). An IPO is the process of taking a private company public and enabling investors to buy and sell the company's shares at any time via the stock exchange. This is an appropriate way for investors to exit because it is very flexible, and the attention from the public can lead to better recognition of the firm. Funds and private investors favour the concept of an IPO because, whilst they might not sell all their shares at once after the company goes public, they can sell them anytime they want. Additionally, as the company matures and hopefully grows, its stock price can reach multiples of its IPO price, increasing the value of its portfolio even further.

3. Literature Review

The authors used in the preparation of this paper other scientific articles and economic theory publications which were then referenced. The study by Foley (1991) on capital markets was employed during the theoretical analysis, along with that by Strumeyer & Swammy (2017).

Weik et al. (2024) focused on the international relocation of startups, and examined startup headquarters' location history based on data from 17 countries. The most significant observation was that most relocations (85%) were directed to the US.

To examine the impact that capital markets have on the economy, the publications of Bekaert et al. (1995), as well as several other articles, were studied, together with works that present and discuss the structure of capital markets and their impact on startup companies. Binh et al. (2020) focused on the capital markets in Korea, whereas Black & Gilson (1998) examined the structural differences between markets in countries such as Germany and the United States. In the econometric section, a brief overview of a paper describing a similar, but far more advanced analysis by Żbikowski & Antosiuk (2021) was included.

For the purposes of this article, a study by Żbikowski & Antosiuk (2021) was discussed in detail. Their research aimed to estimate a supervised machine learning model to predict the success of a business and to measure the significance of the exogenous factors that contributed to it. The applied methodology compared three machine learning techniques to find the best-performing one, i.e. logistic regression, support vector machine, and the gradient boosting classifier. The dataset employed in the research was a very large set of over 200 thousand observations procured from Crunchbase, which is a paid platform that aggregates data about private and public companies. The authors performed an extensive review of advanced econometric literature and concluded that their study was the only one focused on the practical applicability of the model. They concluded that the most effective methodology was the gradient boosting classifier, with a precision score of 57%. They found that the most important factors in predicting the success of a business included: country, region size, if the founder has multiple university degrees, is male, and the size of the city where the company is located. The time between graduation and the creation of the startup by the entrepreneur was also important. These findings suggest that the hypothesis that certain factors about the founder have an impact on the success of the company, might be accurate.

To find better efficiency in venture capital, Kakar (2024) searched for the implications for the startup ecosystem, and concluded that only 20% of venture capital investments yielded the expected returns. Improvement in this area would bring economic growth resulting from investment in innovative companies such as startups. An additional factor considered in the study were the differences in financing depending on the location: Asia, Europe or the USA. In conclusion, the author stated that machine learning algorithms can help determine which startups should be financed and what factors the investor and investee should consider when deciding whether to use external capital.

Shim (2025) aimed to determine the main factors influencing the acquisition of funding from the founder's point of view. In-depth interviews were conducted with representatives of Korean content companies that had raised investment between August 2021 and July 2024. As a result, four main factors contributing to successful fundraising were identified: a) improving investment understanding, b) gaining representative knowledge, c) achieving measurable results, and d) making connections. According to the author, this means that in order to obtain external capital at an early stage of development, content companies must demonstrate quantitative evidence of the company's growth potential based on the experience of the founders and strive to improve the company's digital capabilities.

The paper Venture Capital Booms and Start-Up Financing by Janeway et al. (2021), reviewed the research on the relationship between the observed growth of venture capital (VC) and startup financing. It focused on three issues in particular: the reason for the large increase in new venture capital assets, the effects of this influx mainly on investment opportunities supporting technological innovation by startups, and finally that research findings indicating that venture capital investments were directed at specific industries and geographic regions.

Townsend (2015) also researched the relationship between venture capital firms and startups, focusing on reactions in the event of a negative shock on the financial market. The article on the spread of financial shocks examined how venture capital-backed companies were affected by negative shocks during financial crises. The author estimated the impact of the bursting of the speculative bubble on the market on non-IT companies that were then in venture portfolios. The conclusion was that the likelihood of these companies exiting financing at that time was higher compared to the rest of the companies in the portfolio.

The functioning of startups is a very dynamic process, therefore forecasting trends and measuring success requires the use of innovative research methods. Bennet et al. (2024) proposed the use of an integrated Technology Acceptance Model (TAM) with a robust Random Forest algorithm, thus increasing predictive accuracy, which allowed the use of the following empirical data: revenue growth, capital raised, innovation index and active users. The authors concluded that a comparative analysis with previously used models, such as logistic regression, indicated the superiority of the proposed model, especially in predicting the success of startups.

4. Methodology

An investor contemplating backing a startup company looks for a way to minimise risk so that they maximise their expected return. The expected return can be calculated as the product of the probability of success and the profit made from exiting the investment. An increase in the probability of success, or the profit, would lead to an increase in the expected return. The amount of profit made on an investment, however, is for the most part, out of the investor's control. An easier way to increase the expected return is to increase the probability of success, but for that to be possible, the investor needs to be able to quantify the potential and accurately estimate the probability of success of each possible venture. To do this, it would be necessary to select those startups that have the best potential to be successful. An accurately estimated linear regression model can be an effective tool to do exactly that. In order to predict the possibility of success of venture with startups based on factors selected by the authors, the appropriate method was the Ordinary Least Squares regression (OLS), which is a common technique for estimating coefficients of linear regression equations that describe the relationship between one or more independent quantitative variables and a dependent variable (simple or multiple linear regression), often evaluated using r-squared.

In this section, an OLS model was constructed based on data on startups established in the period 2000-2019. Next, the model was examined and its performance evaluated, before being applied to verify the hypotheses posed in the introduction.

4.1. Functional Form of the Model

The explained variable in this model is the final valuation variable, which is the logarithm of the final valuation variable, or the valuation of the company after the latest funding series. In the analysed dataset, only A or B funding series are available. The explanatory variables are the logarithm of the *initial valuation*, which is either the A-series funding or seed-stage funding, if available. The other explanatory variables are: the number of previously launched startups by the founder (*startup experience*); the logarithm of *tenure* – the number of years of experience that the founder has in their field, and *consulting* – a binary variable showing if the founder has worked in the consulting industry; *teacher* – a binary variable showing if the founder has ever been a teacher, professor or mentor; *director* – a binary variable stating whether or not the founder has been a manager, director or vice president of their previous place of employment; *google* and *microsoft* are binary variables that state if the founder has ever worked in one of those companies, and finally, *sales* – also a binary variable that shows if the founder has experience in the field of sales. Using the aforementioned variables, the functional form of the model can be assembled as presented in Example 2. The logarithms were introduced to the model to improve the quality of the model and minimise the potential for heteroskedasticity to occur. Due to the appearance of logarithms on both sides of the function, this model can be classified as a log-log model.

Example 2. The functional form of the regression model:

$$ln(\text{final}\ \widehat{\text{valuation}}) = \widehat{\beta_0} + ln(\text{initial valuation})\widehat{\beta_1} + ln(\text{tenure})\widehat{\beta_2} + \text{startup experience}\ \widehat{\beta_3} + \text{consulting}\ \widehat{\beta_4} + \text{teacher}\ \widehat{\beta_5} + \text{director}\ \widehat{\beta_6} + \text{google}\ \widehat{\beta_7} + \text{microsoft}\ \widehat{\beta_8} + \text{sales}\ \widehat{\beta_9}$$

where:
final valuation − the valuation achieved during the latest funding round,
initial valuation − the valuation achieved during the previous funding round,
tenure − the number of years of professional experience of the founder,
startup experience − the number of previous startups launched by the founder,
consulting − 1 if the founder has worked in consulting, 0 otherwise,
teacher − 1 if the founder was a teacher, professor or mentor, 0 otherwise,
director − 1 if the founder has previously been a manager, director, or vice president, 0 otherwise,
google − 1 if the founder has worked for Google, 0 otherwise,
microsoft − 1 if the founder has worked for Microsoft, 0 otherwise,
sales − 1 if the founder has worked in sales, 0 otherwise.

4.2. Dataset

The dataset for this model was acquired from Kaggle.com. (a subsidiary of Google), which is a website where data scientists can share datasets with each other. It was created by the user FirmAI, an open--source organization dedicated to educating people in the data science field. The dataset contains two tables, created in 2019. The first one comprises 1206 companies, their founders, and their seat, series A and B valuations. The second table includes 573 entries of detailed information about the founders referenced in the former dataset. The observations in the set dated from 2000 to 2019, and contained *tenure*, *startup experience*, *consulting*, *teacher*, *director*, *google*, *microsoft*, and *sales* variables mentioned in the functional form of the model. The dataset for the purposes of the regression was custom built by joining the two tables using the first name of the founder as a primary key. After combining the tables and cleaning the data from empty records, 453 usable observations were left, with each observation containing the whole set of variables from the two initial tables.

5. Results

5.1. Descriptive Statistics

Before running the regression, it was important to examine the dataset using descriptive statistics and visual analysis. In Table 1, the most important information involved the mean, min, max, and standard deviation.

It can be seen that the average company in the dataset was initially worth around $21.6 million. After the A or B series of funding, the average grew to around $103 million, with the most expensive company reaching a final valuation of $1.63 billion. Noted that the average startup founder in the dataset had around seven years of experience, and the most experienced founder – 24 years.

Table 1. Descriptive statistics of selected variables

Variable	Count	Mean	Std. dev.	Min	Max
Initial valuation	454	2.16e+07	3.04e+07	860000	4.20e+08
Final valuation	455	1.03e+08	1.48e+08	5500000	1.63e+09
Startup experience	457	.7724289	1.114431	0	7
Tenure	457	7.099562	5.343922	0	24
Consulting	457	.2122538	.4093517	0	1
Teacher	457	.3085339	.4623944	0	1
Director	457	.3391685	.4739459	0	1
Google	457	.0656455	.2479328	0	1
Microsoft	457	.0503282	.2188609	0	1
Sales	457	.1203501	.3257271	0	1

Source: authors' elaboration created in STATA.

Graphical analysis can provide a lot of information about the dataset, three items are presented further: the representation of the density of the final valuation variable, the scatterplot of startup experience in regards to final valuation, and the scatterplot presenting the relationship between the initial and final valuation variables.

Figure 2 shows the density of the final valuation, and it can be observed that significant positive skewness and also incredibly high positive kurtosis were present.

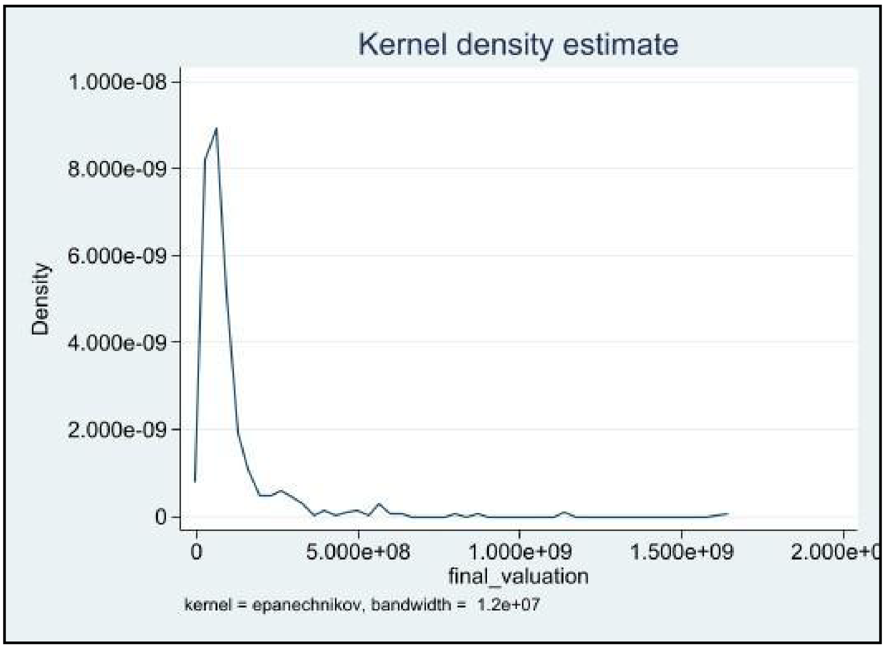

Fig. 2. Approximate density of the *final valuation* variable

Source: authors' elaboration created in STATA.

Figure 3 is interesting because it reveals an a negative correlation between the number of startups established by the founders and the final valuation. This might suggest that the founder created a subsequent startup because the first one did not succeed and closed down. Therefore, the more startups the founder created, the more weary the investors became. This is a useful insight which was easily identified by the use of a simple scatter plot. Additionally, it is clearly visible that the largest startup in the dataset was also the first one for its founder.

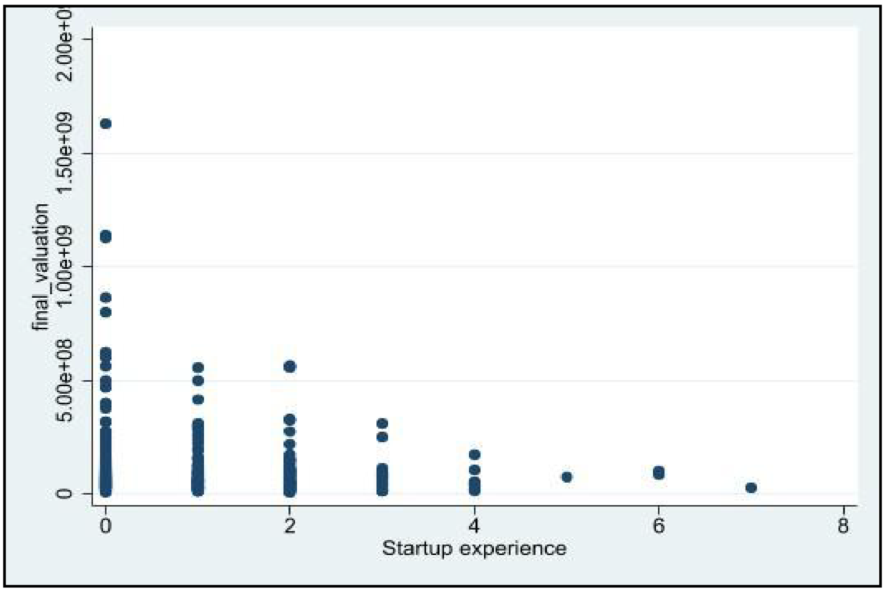

Fig. 3. Scatter plot of *startup experience* and final valuation

Source: authors' elaboration created in STATA.

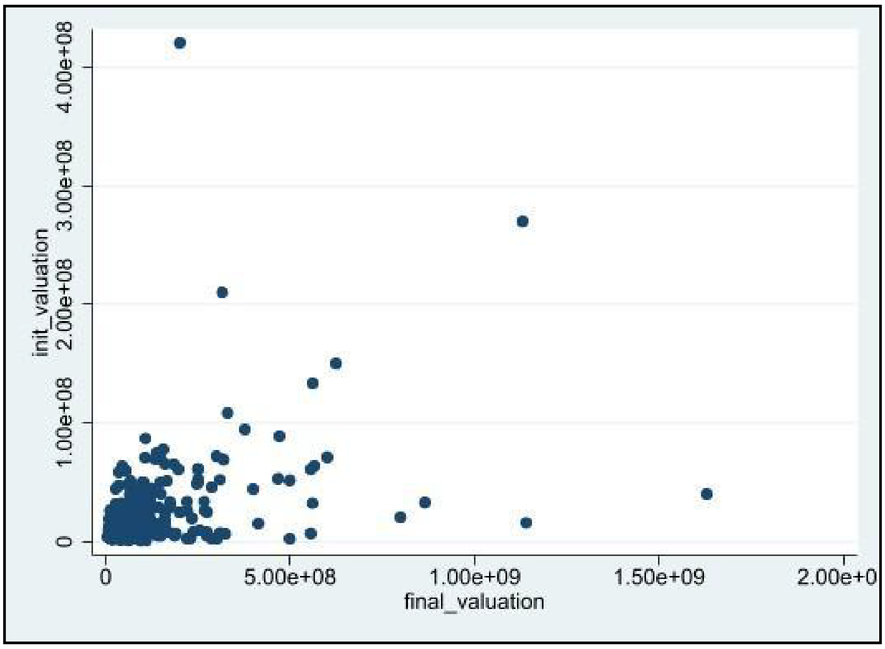

Fig. 4. Scatter plot of *final valuation* in regard to the initial valuation

Source: authors' elaboration created in STATA.

Figure 4 illustrates the relationship between the initial and final valuations. Apart from a few outliers, the vast majority of observations were in a small cluster in the bottom left corner. The scatterplot suggests that there was a positive linear relationship between the two variables.

5.2. Model Regression

After the descriptive statistical analysis, the regression model could be estimated, and the regression results are presented in Table 2. The value of the *F*-test statistic was equal to 14.25, which gives a *p*-value of 0.000, and thus there were grounds to reject the null hypothesis of the *F*-test stating that the model was jointly insignificant, hence it can be concluded that the model was jointly significant. The value of the R^2 metric was 0.2245, with the interpretation being that the model explained 22.45% of the variability of the examined variable. This is a satisfactory level of explanatory power, however, it leaves some room for improvement.

Table 2. Model regression results

ln(*final valuation*)	Coefficient	*t*-statistic	*p*-value
ln(*initial valuation*)	0.4114102	10.220	0.000
Startup experience	-0.0486756	-1.470	0.143
ln(*tenure*)	0.0076396	0.190	0.852
Consulting	-0.0452969	-0.500	0.620
Teacher	-0.1168799	1.450	0.147
Director	0.1608453	2.000	0.046
Google	0.2063727	1.360	0.173
Microsoft	-0.0487489	-0.290	0.773
Sales	-0.2023325	-1.750	0.081
Constant	11.19415	16.940	0.000

Source: authors' elaboration created in STATA.

The *p*-value of the *t*-statistic for statistical significance was larger than the significance level of 0.05 for all variables except the constant, the initial valuation, and the director variable. Therefore, it was not possible to state that the variables startup experience, namely the logarithm of *tenure*, *consulting*, *teacher*, *google*, *microsoft*, and *sales*, were statistically significant. The only statistically significant variables in the model for the 0.05 significance level were the above-mentioned variables: *constant*, the logarithm of the *initial valuation*, and *director*. The coefficients of those variables can be interpreted in the following way: an increase in the *initial valuation* of 1% will lead to an increase in the final *valuation* by 0.41%. Consequently, if a startup founder has been a manager, director, or vice president of their former place of employment, the final valuation will increase by around 16.08%. This is expected behaviour and this could be so because the experience of the founder positively reinforces the investors in the fact that they can lead the company to success. For a significance level of 0.90, the *sales* variable can be considered as statistically significant and interpreted in the following way: if the founder has worked in sales, the final valuation will decrease by around 20.23% – this behaviour, however, was not expected. Any other coefficient could not be interpreted as the rest of the variables were not statistically significant.

5.3. Diagnostic Tests

To verify that the estimation met the assumptions of the linear model, diagnostic tests for heteroskedasticity, omitted variables, normally distributed residuals, and collinearity had to be performed. The significance level of 0.05 was chosen.

To test for heteroskedasticity, the Breusch-Pagan test and the White test were used. The test statistic of the BP test amounted to 2.90, whilst the *p*-value was 0.0887. Since the *p*-value was larger than the adopted significance level of 0.05, it can be concluded that there were no grounds to reject the null hypothesis of the BP test that there was constant variance. Thus the conclusion that the problem of heteroskedasticity was not present in the model was true, and the assumption of the linear model was met.

It can be confirmed with the results of the White test; the test statistic was 59.83, making the *p*-value 0.1175. The *p*-value was again larger than the critical value, hence there were no grounds to reject the null hypothesis of homoscedasticity.

After conducting the Ramsey RESET test for omitted variables, the following results were obtained: test statistic equaled 9.69, and the *p*-value amounted to 0.0000. From this, it can be stated that there were grounds for rejecting the null hypothesis, namely that there were no omitted variables from the model. This leads us to the conclusion that there were problems with the functional form of the model.

Next, the Jarque-Bera test was conducted to verify the normal distribution of residuals. The results were as follows: the *p*-value was 0.000 for all the variables, except for the initial valuation of 0.2825. Thus there were grounds to reject the null hypothesis of the Jarque-Bera test for all variables, except the former for the chosen significance level. The null hypothesis of the test stated that residuals were normally distributed, the conclusion reached was that residuals were not normally distributed, except for the initial valuation variable.

To test for multicollinearity, the Variance Inflation Factor was calculated for all the variables used in the model. The mean VIF reached 1.04, where the maximum VIF of 1.10 was obtained for the logarithm of the tenure variable, and a minimum of 1.01 for startup experience. All the other variables had a low VIF of around 1. The results suggest that the variables were not correlated with each other, therefore the problem of multicollinearity was not present.

5.4. Conclusion of the Econometric Result Section

In this section a log-log model was estimated using the OLS method. The dataset containing observations of startups established from 2000 to 2019 was imported, cleaned, and examined using descriptive statistics and graphical analysis in STATA. Then, the regression was estimated, and the model examined in terms of the assumptions of the OLS model, as well as statistical significance. The model was jointly significant, however all but three variables were statistically insignificant for a significance level of 0.05. The model was free of heteroskedasticity and multicollinearity; however, the problem was found with the functional form of the model, and the residuals of not all the variables were normally distributed. Despite the mentioned problems, it can be concluded that factors such as the previous valuation, and the background of the founders, e.g. past employment, had an impact on the success in obtaining more capital for the company

6. Discussion and Conclusion

The background to the study is related to the unique situation in which startups find themselves when it comes to raising new capital, especially since it takes place almost exclusively through the sale of the company's own shares. The research gap covers investors' approach to these startups as it involves a higher risk of return on capital. The paper's aim was to examine selected conditions for raising capital from investors by start-up entrepreneurs. As a methodology used to obtain the result, an OLS model was constructed based on data on startups established in the period from 2000 to 2019.

The research hypothesis was that "information such as the founder's background, education, experience, and amount of funding acquired previously has a positive impact on the amount of capital that will be acquired in the next rounds of funding". The key research findings confirmed this hypothesis. The model's joint statistical significance suggested that the explanatory variables had an effect on the explained variable, even if some of them were statistically insignificant.

At the same time, the key findings included the fact that some of the factors studied showed low significance. These factors belonged to one group of variables (type of profession of the startup founder: consultant, teacher, Google or Microsoft employee). However, in this set, only the profession of director was a significant factor. Such an observation is important in the context of the observed research gap.

The implications of the results of the conducted study will be useful for practitioners in the context of assessing their own possibilities of obtaining new capital for a company without a relevant history of operation, in particular the assessment of whether the selected factors proposed by the authors have a positive impact on the success of obtaining capital by a startup on the capital market. The possible consequences of the study's findings are also of interest for researchers in terms of seeking another set of unconventional variables, which will further expand the knowledge of startup owners. The authors' direct contribution is the proposed unique set of factors used to assess the success of increasing equity capital.

The limitations of the study were the scope of the database and the method used, limited in comparison to the latest cutting-edge solutions available to data scientists. Nevertheless, the results of the estimation gave sufficient grounds to confirm the research hypothesis. It is suggested that future research should be directed towards increasingly simple applications of machine learning methods.

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Czynniki wpływające na skuteczne pozyskiwanie kapitału przez startupy: przykład z amerykańskiego rynku kapitałowego

Streszczenie

Cel: Niniejszy artykuł ma na celu analizę wybranych czynników, które mają wpływ na sukces pozyskania kapitału przez startup na rynku kapitałowym. Omówiono następujące pytanie badawcze: czy informacje takie jak pochodzenie założyciela, wykształcenie, doświadczenie i kwota pozyskanego wcześniej finansowania mają pozytywny wpływ na kwotę kapitału, która zostanie pozyskana w kolejnych rundach finansowania?

Metodyka: Przeprowadzono analizę ekonometryczną, badając wpływ doświadczenia i pochodzenia przedsiębiorcy na sukces kolejnych rund finansowania, przy użyciu modelu regresji liniowej OLS. W badaniu wykorzystano wybrane czynniki analizowane na podstawie danych z rynku amerykańskiego.

Wyniki: Łączna istotność statystyczna modelu sugeruje, że zmienne objaśniające mają wpływ na zmienną objaśnianą.

Implikacje i rekomendacje: Wyniki te mogą być ważne dla nowych startupów, które chcą uzyskać zewnętrzne finansowanie z rynków kapitałowych. Podsumowując, ten problem badawczy koncentruje się na początkowej sytuacji finansowej startupów w oparciu o dane z USA.

Oryginalność/wartość: Główną wartością badania jest identyfikacja czynników, które okazały się mało istotne (rodzaj zawodu: konsultant, nauczyciel, pracownik Google lub Microsoft) oraz tych (zawód dyrektora), które są czynnikiem istotnym.

Słowa kluczowe: startupy, rynek kapitałowy, *venture capital*