“WHAT FACTORS AFFECT

THE VALUATION OF US STARTUPS”

by

Oleksandr Gorbach

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Thesis Supervisor:

Professor Olesia Verchenko

Approved by: Head of the KSE Defense Committee, Professor

Date: ___________

Kyiv School of Economics

Abstract

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The venture capital market experienced a boom in 2021 followed by a steep funding decline in 2022, which can be compared to a dotcom crash. At the same time, existing studies studied only earlier market developments. In this study, the author has gathered the latest available dataset for the US, which still remains the main receiver of venture funding. By using the GLS model, the author shows how various factors regarding the startup affect its valuation after the round. The study shows that Silicon Valley is losing its importance as a venture hub, while another hub, New York, has growing importance. The author's data also shows that the cryptocurrency industry received a valuation premium in 2022, while other popular industries among VCs do not have it. Furthermore, the research provided evidence that receiving funding from top-tier investors has a positive impact on valuation, while the age of a startup has the opposite effect. Therefore, the research focuses on providing valuable information for both startup founders and investors on primary factors affecting the most important figure in their work, the value of the company.

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LIST OF ABBREVIATIONS AND TERMS

VC Venture Capital

B2B Business to Business

B2C Business to Customer

M&A Mergers and Acquisitions

a16z Andreessen Horowitz

FinTech Financial Technology

AI/ML Artificial Intelligence and Machine Learning

HQ Headquarters

E-commerce Electronic Commerce

Series A/B/C… A funding round of the company with a ready product. The letter means the round number starting from

C h a p t e r *1*

INTRODUCTION

Venture capital investment was booming in 2020 and 2021 when startups raised $383.4B and $671.3B respectively. However, 2022 became the year of cool-off, in the first half of the year startups raised $281.8B (Crunchbase, 2022). The volume is higher than in 2020, but it already lags behind 2021 figures significantly. The US, and especially Silicon Valley, remains the main place, where startups emerge, corresponding to 49% of the total VC funding worldwide. So far there were attempts to analyze, what impacts the startup valuation the most during its life as a private company. However, all these attempts were done on quite limited datasets and were studying the industry state before or at the start of the boom, which exceeded by value invested in the Dotcom era. Given the larger and wider data available on startups, this thesis aims to understand what factors affect the valuation of startups the most. Among other factors, the author distinguishes the geographical effect, the fact that startups receive higher valuations, if they reside in certain locations, due to the extensive network of other entrepreneurs and ease of receiving capital in those areas. Another important element that can skyrocket a company's value is the fact that it attracts money from so-called tier-1 investors, a short list of the most successful venture capital funds in the world that invested in the current largest public software companies, e.g., Andreessen Horowitz, Tiger Global Management, or SoftBank Investment Advisors.

In the venture capital world, the purpose of startup valuation is to give the company a fair value, an asset's sale price agreed upon by a willing buyer and seller, assuming both parties are knowledgeable and enter the transaction freely, which is crucial for both sides (Investopedia, 2022). For investors, it is important, as they do not want to overpay for the equity they invest in, and their purpose is to maximize future returns of limited partners that invest in their funds. For startup founders, it is crucial, as during the investment round they do not want to sell part of their company for cheap in exchange for invested capital and support from an investor, as the value of the company is directly related to their wealth.

The objective of this study is to find out how different factors affect the startup valuation and what factors are the most important. Valuation is one of the most important indicators of the company's perspectives, as despite it being based on fundamental financial ratios, it is heavily affected by expectations of the company's future profits, especially in the startup world, where companies without revenue can cost billions of dollars. It is worth noting that previous studies on this topic had limited datasets, due to the nature of the companies they study. Startups are private companies that are not required to report their financial data to the public. Therefore, there is little info about their financial strengths. Financial data is usually known by venture capital funds, that invested in that startups, but it is confidential info. Therefore, financial information can be known to the public, only when the private company decides so. For this reason, there exists special databases devoted mainly to private equity research and parse open information on the web, like Pitchbook, that I use, CB Insights, or other sources. As these databases have a steep price and business orientation, they were not used by authors of previous academic studies in this area. Therefore, the application of data from such databases as Pitchbook can provide valuable insights into the startup industry, that were not covered or had limited coverage in previous research.

This research is an extension of previous academic studies, including the work of Vadym Chernikov (2021) from the Kyiv School of Economics. Even though the author's research includes some variables from previous studies, it adds factors that were not included in previous studies.

For the research, the author used a standard OLS regression, which after heteroscedasticity checks was substituted for GLS, which is fairly common for such studies. The choice of GLS over heteroscedasticity-robust standard errors was motivated by the importance of precise estimators, as any inaccuracy in determining valuations may affect investor returns.

The results of the research showed that there is a positive effect of launching a company in New York and California, while there are no such effects in Texas. Industry data showed that only cryptocurrency startups receive a valuation boost and there is no impact of the SaaS business model on valuation. Pretty much expected the effect of participation of top VC funds and growing round series had a positive impact on valuation. Though the effect of age of a company was rather unexpected, younger companies are more highly valued.

The results of this study are of equal interest to academic researchers and the venture capital public. For the former ones, it is important, as it is an unpopular topic in the research due to the limited volume of data and quite small industry size before last year's boom. For the business public, this study provides another, more thorough and extensive view of hypotheses that are generally used in venture capital, as usually its representatives do not use any modeling and rely on a gut feeling when choosing deals to invest in.

This thesis consists of 6 chapters: introduction, literature overview, description of the methodology, description of the data, results, and conclusions and recommendations.

Chapter *2*

LITERATURE OVERVIEW

2.1 Academic research

As a venture capital topic is mostly bypassed by academia a brief review of the existing literature within this industry is necessary to demonstrate, how the research evolved through time. Even though the scope of research was limited on this topic, several valuable recent studies contributed the most to the research. However, due to the strong business orientation of the venture capital industry, it is equally important to review business research provided by market leaders in this industry.

Among others, Miloud, Aspelund, and Cabrol (2012) performed a quantitative investigation of the influence of non-financial, strategic factors on the actual valuation of French startups and proposed an alternative strategic analysis to value the company. In their study, they found that the age of a company is an important determinant in explaining the pre-money valuation of a startup. Also, they found a positive effect on the valuation of the market size and revenue growth of the company.

Hsu (2007) investigated the sourcing and valuation of venture capital among entrepreneurs with varying levels of prior startup founding experience, academic training, and social capital. The result was that entrepreneurs with previous founding experience can negotiate better the valuation of their next company, as well as larger academic capital, which is positively related to the higher value of the founded company.

Gompers et al. (2009) present evidence that entrepreneurs with a track record of success are much more likely to succeed than first-time entrepreneurs and those who have previously failed. Though unlike Hsu (2007) the author presented evidence that venture capital firms do not pay premiums for the availability of previous founding experience.

Armstrong, Davila, and Foster (2006) study the effects of financial statement information on startup valuation and argue that some costs, considered value-diminishing for public companies are value-enhancing for startups due to a strong investment aspect. Also, unlike the perceptions of the industry professionals they argue that public market indices have a significant impact on startup valuation.

Therefore, as there are few studies on the venture capital industry there is space for novel approaches and new hypotheses testing, and the author will use them to discover new insights into such an underestimated industry.

2.2 Business literature overview

In a quarterly report on the venture capital industry, Crunchbase studies the developments of the venture capital industry in the second quarter of 2022. Authors argue that global funding slowed down dramatically, mainly due to the rapid decline of late-stage deals volume. The funding reached $120B, which is 26% lower than $162B in the first quarter of 2022, and 27% lower than $165B in the second quarter of 2021 (Figure 1). The largest impact was on late-stage deals, which is Series C+, and which fell by 31% quarter over quarter while constituting almost half of investment volume. Early-stage and Seed deals also declined quarter over quarter but at a lower magnitude, while Seed deals even showed year-over-year growth. However, these figures should not be perceived as representing the real state of the market in the second quarter. The main reasoning is that investment deals before being closed are going the way of analysis, due diligence, and negotiations. Therefore, we can safely assume that the second quarter statistics represent the market sentiment of the first quarter.

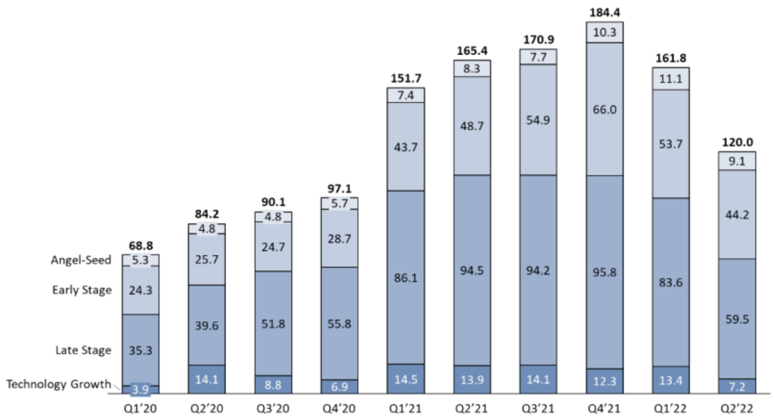

Figure 1. Venture Capital market statistics

CB Insights in The State of Venture Q3'22 Report spotlights that US-based companies account for 49% of global funding, leaving the US as a global venture capital leader. The majority of funding was raised in 2 main VC hubs in the US, Silicon Valley, and New York. Though it is worth noting that funding of startups in Silicon Valley reached an 11-quarter low, showing its decreasing role as a venture hub. Another important statistic presented in the report is the list of the most active investors. Compared to Q2'22, when Tiger Global Management and 2 other VCs each invested in 109 companies, the Q3'22 top result was received by a16z, which invested only in 44 companies (Table 1).

Another important statistic is the deal size, which also experienced a decline this year. The global average deal size was $18M, a 28% decline from $25M in 2021, while the median size stayed at the same level of $4M. For the US, the median deal size is slightly higher than for the rest of the world, $5M. However, this statistic includes all deals, Angel, VC, Private Equity, Asset

Management, and Corporate. The median deal size for the VC industry only is $9M, a decline from $11M in 2021.

Table 1. The most active investors in Q2'22

Investor	Company count	Country
a16z	44	US
SOSV	41	US
Sequoia Capital China	30	China
Insight Partners	29	US
Accel	27	US
Lightspeed Venture Partners	26	US
Plug and Play Ventures	26	US
East Ventures	25	Indonesia
Goodwater Capital	25	US
FJ Labs	22	US

Unicorn, a startup with a valuation of $1B+, birth also suffered this year. The drop was especially large in Q3'22 when only 25 unicorns were born globally, while in Q2'22 – 87, and in the peak Q4'21 – 141. However, as the IPO activity was also low, the overall number of unicorns worldwide reached 1,192. Out of 25 new unicorns, 14 were born in the US, 7 – in Asia, 3 – in Europe, and only 1 – in LatAm.

An interesting statistic was gathered for mega-rounds, rounds with a $100M+ size. These rounds constitute a small number compared to the whole number of investment rounds, but in terms of funding, they have a significant share. In Q3'22, their share reached 40%, the lowest result in 9 quarters, a drop from 47% in Q2'22, and the peak of 61% result in Q1'21. This number is an additional confirmation of the average round decline and the general cool-off of the VC market.

In general, the whole market shows signs of a cool-off after a booming 2021. After setting records in every indicator possible, the market is returning to 2020 figures, which are still higher than in any year after the 2007-2008 Financial Crisis. The only notable characteristic of the current VC market is the declining role of Silicon Valley, which started after the COVID-19 outbreak and resulted in the growth of other VC hubs in the US, which stays the leader in the VC market.

Chapter *3*

METHODOLOGY

3.1 Choice of variables for the regression analysis

The main question that the author wants to answer is what factors affect the valuation of the startup the most, which is of crucial importance for both investors and startups. For investors, it is important as these factors can ease the analysis and choose companies with certain characteristics, that might ensure high returns. For startups, it is important during the start of their path, as the founder can choose an industry and business model that has the highest chance to become a multi-billion company.

The choice of variables was motivated by the available database, Pitchbook, which has the largest set of data on private companies, and by the literature review conducted by the author. As the dependent variable, the author will use a pre-money startup valuation, which equals the announced amount of valuation minus the money invested at the financing round, which is considered a common practice in the venture capital industry to describe the company value.

For independent variables, the author will choose the data available on Pitchbook and will make some transformations to receive the necessary dummy variables. For investment factors, the author includes the number of active investors, and round information, including its size and number of previous rounds. Also, several dummies representing the most acknowledged venture capital funds, including Andreessen Horowitz, Tiger Global Management, and SoftBank Investment Advisers, will be included to study if there exists an effect of top-tier investors' participation on the company valuation during that round.

The preliminary hypothesis of the author suggests that the startups located in Silicon Valley and newer startup hubs, like New York and Texas, are receiving a valuation premium, compared to the companies from other regions of the US, representing an entrepreneurship network effect due to the high concentration of experienced and supportive mentors in the region, as well as the presence of strong VC investors. This hypothesis is based mostly on the industry perception that companies from other regions of the US have less access to venture capital investment and that in the chosen locations reside the most innovative corporations, willing to incorporate new products into their daily processes.

Due to the recent market developments, we also suggest that startups that received funding from tier-1 investors will have a higher share price. This fact may be dual, as from one side these companies are considered to be the most prominent ones and have the highest chance to become successful and profitable, so investors are willing to pay some initial premium for future success. On the other side, these prominent companies usually receive dozens of investment offers, and they have the negotiating power to dictate terms for investors. Usually, only tier-1 investors, who have the deepest pockets can pay such premiums for the investment opportunity.

The author took some other hypotheses from previous research papers on the venture capital industry. They include the positive effect of the large markets, which is studied by separating industries, where the startup operates. For the current study, the FinTech, Cryptocurrency, and E-commerce sectors are taken as the largest markets with $100B+ annual revenue each in the US only. Investment in FinTech and E-commerce is booming for the last several years, while Cryptocurrency is booming since 2021. Such an increase in investment may be a consequence of the investor perception that these industries will shape the future markets and their willingness to participate in their growth.

Another factor that can affect the valuation is the chosen business model. In the available dataset, it is possible to distinguish companies that have the SaaS business model, which is considered to be the most valuable in the modern world, as these companies have the highest net profit margins among other industries, above 70%. It also relies on long-term one-year or three-year contracts, especially from enterprise customers, which allows businesses with this business model to avoid declines in revenues during crises, which makes these companies quite predictable. For these reasons, they are considered safe bets by investors, as the chance of negative returns is significantly lower than from businesses with other business models.

Also, the author will include the info on the total money raised. The hypothesis here is quite obvious, the more startup raises money the more valuable it is. To further research this question the author also chose round series as dummies. Round series is the number of rounds that the company is raising. The larger letter the more late-stage the company is. Therefore, some early-stage companies might be raising rounds at higher valuations than their more late-stage counterparts.

A number of investors are also included as an independent variable. The logic behind this decision is that investors usually offer their services and networks to assist startups. So, the company that is able to attract investments from a larger number of investors, has access to a larger number of these services.

The last factor that the author researches is the age of a startup. It is chosen to see, if the investment boom in 2021 positively affected the valuation of young companies and if this effect wore off in 2022.

3.2 Model choice

For the analysis, the author will choose OLS as the main model, as it showed its universality in previous studies. However, in papers on this topic it is common to see firm-specific heteroscedasticity and autocorrelation, so to diagnose heteroscedasticity a Breusch-Pagan Test and White Test will be used. In the case of confirmed heteroscedasticity, the author will estimate the GLS model, as it was also used in previous research. To test for autocorrelation the authors will examine the correlation of variables included in the regression and will omit those having a high or medium level of correlation.

Summarizing the discussion above, the equation below represents the model to be estimated in the empirical analysis. The log-linear regression was chosen to receive valuation changes in percentages, which is more comprehensible compared to raw changes in US dollars.

$$\begin{aligned}
&\log(valuation) \\
&= \alpha + \beta_1(total\ money\ raised) + \beta_2(age\ of\ startup) \\
&+ \beta_3(number\ of\ active\ investors) \\
&+ \beta_4(tier-1\ investors) + \beta_5(industry) \\
&+ \beta_6(business\ model\ ) + \beta_7(location) + \beta_8(series)\ (1)
\end{aligned}$$

Also, Table 2 below shows expected by the author signs of independent variables. He hypothesizes that all variables will have positive signs, which corresponds to the general VC industry views on startups.

Table 2: Summary of variables and their expected signs

Variable name	Expected sign	Description
Valuation	N/A	The dependent variable, pre-money startup valuation
Total money raised	+	Total capital raised by a company during all investment rounds
Series	+	The round number the company is raising
Age of startup	+	Years since the company was founded
Number of active investors	+	A number of investors participated in equity rounds
Tier-1 investors	+	Dummies that are equal to 1, if one of the chosen investors invested in the startup, 0 otherwise
Industry data	+	Dummies that are equal 1, if the startup is doing business in fintech, e-commerce, or blockchain, 0 otherwise
Business model	+	Dummy that is equal to 1, if the company has a SaaS business model, 0 otherwise
Location	+	Dummies that is equal to 1, if the company is registered in California, Texas, or New York, 0 otherwise

Chapter *4*

DATA DESCRIPTION

The main source of the research data is Pitchbook Data, the largest provider of data on private and public companies, which specializes in researching global M&A, private equity, and venture capital investments along with all participating investment parties. The dataset downloaded from Pitchbook consists of 1,624 observations of startups that have their headquarters registered in the United States. As the total number of companies with such characteristics lies well beyond 1,624 observations, the initial dataset was filtered to omit missing data and to cope with downloading restrictions imposed by Pitchbook, which at the available subscription had a 2,000 datapoints limit. The data was cleared according to the below filters:

1) All companies that had N/A in one of the dependent and independent variables were deleted from the initial list
2) Only startups having headquarters in the United States were chosen, as it is the soundest venture capital market, and its developments are then distributed in other markets only in several years. So, to present recent market developments only 1 market was chosen
3) Only startups that raised money in 2022 were used in our analysis. There were several reasons for that. First, we want to present the most recent developments of the venture capital market and by separating 2022 we can see the developments that are inherent to current venture capital cool off after the booming 2021. Second, in our analysis, we wanted to see only relevant companies that can raise new financing, as according to business practice, the company that can't raise money every 1-2 years is considered to be unsuccessful and

if it did not raise for 2+ years, it is nearly impossible to raise a new round. The third reason lies within the limitations of the Pitchbook database

4) Startups with a valuation of less than $10,000 and that raised less than this sum were deleted from the dataset, as they are not representative in terms of the total market, as most startups are usually receiving at least $1,000,000 valuation after the first fundraising, while for the US this figure is closer to $5,000,000
5) Startups that raised at least a Series A round was chosen for our analysis. This step allowed to filter out companies that raised debt financing, when valuation is not assigned to the company, though it may be reported in the dataset as valuation from the last equity round. Also, we omitted startups that were acquired or merged with other companies, as our target was to research the state of the venture capital market, not the M&A market. We filtered out startups that were raising Pre-Seed and Seed rounds. These rounds are not representative in terms of the whole venture capital market, as these startups are in the idea stage, and a somewhat standardized valuation is assigned to them which is not related to the company's performance.

After filtering out companies the author was able to download information about 1,624 companies, that were used in further research. Table 3 presents a summary of the dataset:

Table 3: Descriptive statistics on the dataset

Variable	Min	Mean	Median	Max	Number
Valuation, $M	1.16	413.35	118.25	12,590	-
Total money raised, $M	0.5	91.71	37.78	2,035.10	-
Number of active investors	1	13.55	11	155	-
Age of startup, years	0	5.78	5	28	-
Cryptocurrency/ Blockchain	-	-	-	-	82
Fintech	-	-	-	-	226
E-commerce	-	-	-	-	106
a16z	-	-	-	-	81
Tiger Global	-	-	-	-	74
SoftBank	-	-	-	-	31
SaaS	-	-	-	-	474
California	-	-	-	-	724
New York	-	-	-	-	210
Texas	-	-	-	-	63
Series A	-	-	-	-	785

Table 3: Descriptive statistics on the dataset (Continued)

Variable	Min	Mean	Median	Max	Number
Series B	-	-	-	-	460
Series C	-	-	-	-	213
Series D	-	-	-	-	94
Series E	-	-	-	-	38
Series F	-	-	-	-	26
Series G	-	-	-	-	4
Series H	-	-	-	-	3
Series I	-	-	-	-	1

The dataset contains companies with a valuation from a mere $1.16 million in the case of Life Science Marketplace to $12,590 million, a valuation of Faire, while the mean valuation in the dataset is $413.35 million and a median – of $118.25 million, showing skewness due to several companies with huge valuations.

Obviously, the total raised data should be smaller than the valuation data, as the company can't raise more money than it costs. However, it is possible in rare cases, when the company experiences a down round, a round when the valuation is lower than in the previous one. In our dataset, there were 6 such companies. In the whole dataset two companies raised $0.5 million in total, Life Science Marketplace and Maxwell Biomedical, while Anduril raised $2,035.10

million. The median of $37.78 million is lower than the mean of $91.71 million for the same reason as with valuation.

Also, we gathered age statistics for these companies and received the following results: the youngest company age is 0, meaning that it is founded in 2022, while the oldest one is 28 years old. The median does not differ from the mean, which is 5.78 and 5 years respectively.

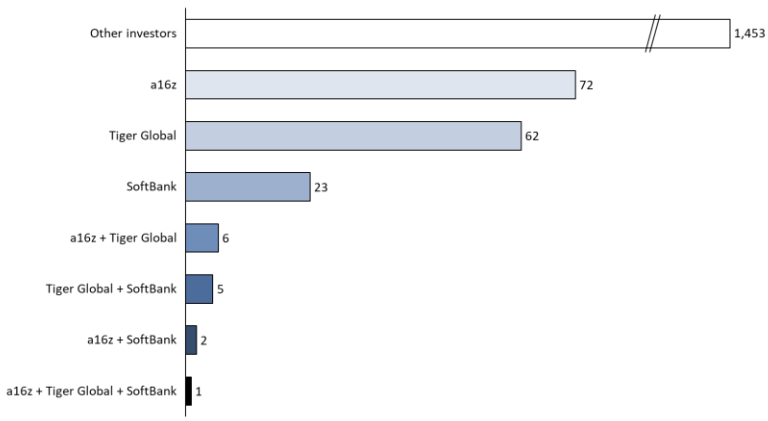

Figure 2: Investor statistics

To define the impact of the participation of top-tier investors on the companies' valuation we gathered investors' statistics. Their number varies from 1 to 155, with a mean and median of 13.55 and 11 respectively. Among all investors, we chose three, Andreessen Horowitz, Tiger Global Management, and SoftBank Investment Advisers, which are considered the best ones. The reason to choose these particular investors is their huge activity in the last years, which resulted in extensive media coverage. In our dataset, 81 startups raised money from Andreessen Horowitz, 74 – from Tiger Global Management, and 31 – from SoftBank. Though some startups raised money from both or even three of these investors, which can be seen in Figure 2

In our analysis, we research if the operation in Fintech, Blockchain, and E-commerce industries and SaaS business model affect the valuation. Among 1,624 startups there are 82 operating in the Blockchain industry, 226 – in Fintech, and 106 – in E-commerce. Also, 474 startups have a SaaS business model. Similar to investor data, there are intersections between industries and businesses, which are presented in Figure 3.

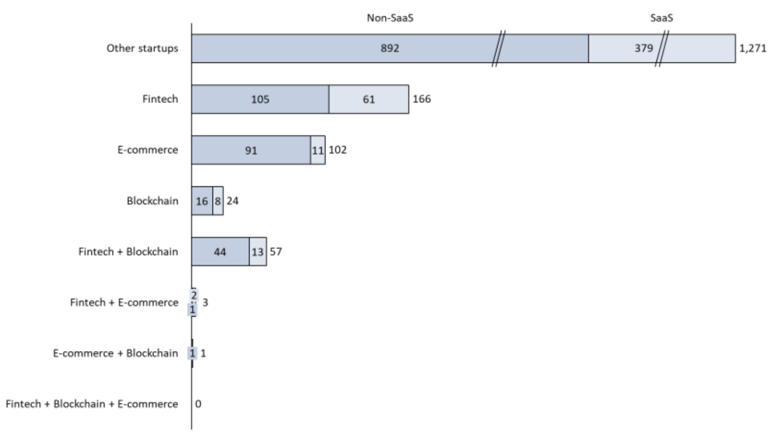

Figure 3: Industry and Business model statistics

The geographic distribution of startups is somewhat expected. Almost half of the startups, 724, are headquartered in California, where Silicon Valley is located. New York, a destination actively chosen by Blockchain startups was chosen as a headquarters location by 210 companies. Texas, a new destination for startups seeking to avoid the high taxes of California, is a headquarters location for only 63 startups (Figure 4).

Round data that we gathered includes rounds from Series A to Series I. The further the letter is from the start of the alphabet the more mature the company is. Letters correspond to the number of the round, with A usually being the first round of the company with the working product and some traction to show. Commonly, the company starts seeking to become public after raising round D. Though in recent years companies chose to stay private longer, so we see a sharp decline in the rounds only after Series F (Figure 5).

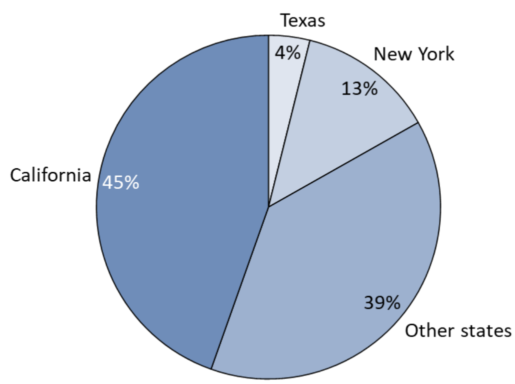

Figure 4: Startups' geographical distribution

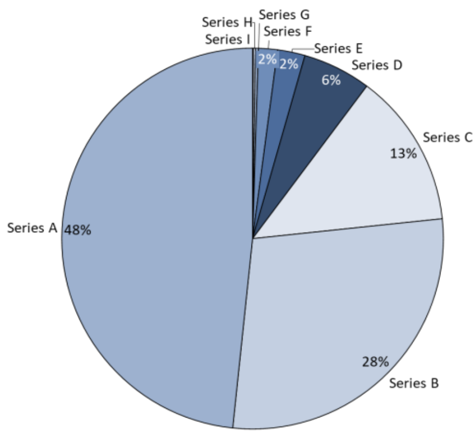

Figure 5: Startups' round data

Before building the model the author checked all variables on multicollinearity. The check was conducted with variables that were assigned to our model. The results are presented in a correlation matrix (Figure 6).

The dependent variable, Valuation, has a strong correlation with 2 variables Total.Raised and Last.Round.Size. Both these variables represent the total and last round volume of investments the company received respectively. And these variables are directly related to the company's valuation, so there is a strong positive correlation with the Variable valuation. Therefore, to avoid multicollinearity the variable Total.Raised was omitted from the author's final regression. Also, there is a weak positive correlation between Valuation and Investor.Number, is the variable representing the total number of active investors in the company. Though its magnitude is not very large we assume that Investor.Number won't cause any multicollinearity issues. All other variables are mostly uncorrelated, so they also can't cause multicollinearity.

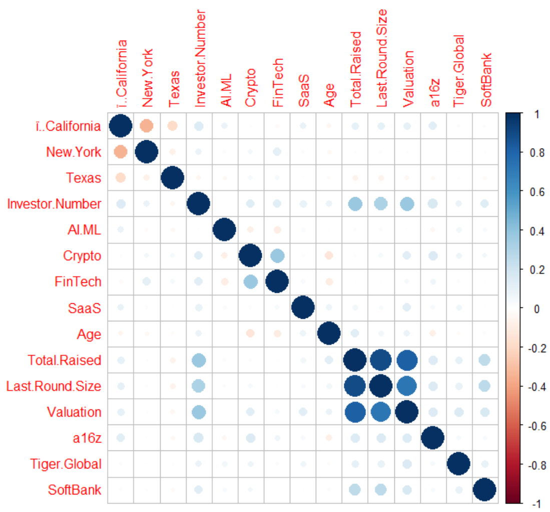

Figure 6. Correlation matrix

Chapter *5*

RESULTS

5.1 OLS regression results

The final OLS regression includes Valuation as a dependent variable, age of a startup, number of active investors, industry, business model, geographical, investor, and series data as independent variables. Variables related to the volume of raised money were omitted to avoid multicollinearity. The results of the regression can be found in Table 4 below.

As the regression is log-linear we should exponentiate the coefficient, subtract one from this number, and multiply it by 100. Thus we will receive the percent change of the dependent variable for every unit increase of the independent variable.

Commented [E1]: That's not true. Read Gujarati, 6.2 Semi-log models. You do not have to exponentiate anything to get percentage change in depedent variable. You just have to mupltiple by 100 to get a growth rate.

Commented [AG2R1]: But that is only true for small percentage changes, as it is an approximation. In Wooldridge 6.2a it is described like these. Multiplying by 100 gives a consistent but not unbiased estimator. While we compound small estimators or simply have a large percentage change there exists a large discrepancy between logarithmic approximation (*100) and the real change

The regression results show us the age of the startup negatively affects the company's valuation. Therefore, the older the company, the lower valuation it has on the same fundraising round compared to the younger company. Therefore, all things equal, the company that is, for instance, raising a Series A round will receive an 8.3% lower valuation than the company that is 1 year older. These results show that the 2021 boom transformed the VC industry, and even after the decline in 2022 younger startups are favored by investors.

Industrial data is a bit surprising, as only crypto startups have a premium when raising venture money. Coefficient values for FinTech and AI/ML companies do not have any significance level. Such a result may be a sign of high deal competitiveness and investor faith in the most recent trends. FinTech and AI/ML industries were booming for several years before 2022 and might have reached a plateau in funding that resulted in a reduction and ultimately the absence of premiums for startups from these industries.

Table 4. OLS regression results

Coefficients	Estimate	Std. error	t value	Pr(>|t|)	Significance
(Intercept)	4.184	0.056	74.605	0.0000	***
Age	-0.077	0.007	-11.510	0.0000	***
Crypto	0.497	0.112	4.438	0.0000	***
FinTech	-0.0180	0.070	-0.257	0.797	
AI/ML	0.056	0.057	0.988	0.323	
SaaS	0.127	0.050	2.561	0.011	*
a16z	0.643	0.105	6.101	0.0000	***
SoftBank	0.780	0.168	4.634	0.0000	***
Tiger Global	0.528	0.109	4.836	0.0000	***
California	0.286	0.050	5.684	0.0000	***
Texas	-0.093	0.119	-0.786	0.432	
New York	0.234	0.073	3.225	0.001	**
Series B	1.150	0.054	21.199	0.0000	***
Series C	2.002	0.073	27.352	0.0000	***
Series D	2.671	0.105	25.459	0.0000	***

Table 4. OLS regression results (Continued)

Coefficients	Estimate	Std. error	t value	Pr(>|t|)	Significance
Series E	3.224	0.155	20.773	0.0000	***
Series F	3.572	0.185	19.285	0.0000	***
Series G	3.880	0.451	8.612	0.0000	***
Series H	4.009	0.530	7.563	0.0000	***
Series I	2.964	0.899	3.296	0.001	**

* statistical significance at the 95% confidence level, ** 99% confidence level, *** 99.9% confidence level

The SaaS business model's positive impact on valuation was quite expected, though a t-value of 2.561 is lower than the t-values of previous and future variables. The subscription model that relies on long-term contracts that do not depend on usage logically is favored by investors, as it allows businesses to avoid revenue declines during crises.

The fact that a startup receives money from top-tier investment funds is also represented by a positive sign of all independent variables related to these funds with high values of t-value. If a startup receives money from a16z, SoftBank, or Tiger Global, it should receive 90.2%, 117.9%, or 69.6% higher valuation respectively.

The impact of the HQ location brought us quite interesting results. Registration in Texas has neither a positive nor negative impact on valuation. While both California and New York positively affect the valuation. California startups have a 33.1% higher valuation on average, while New York startups – have 26.4%.

The positive effect of raising the latter rounds was quite obvious and it was confirmed by positive values of variables with very high significance levels. Only the value for the Series I round is lower than the value for the previous round, but it is the result of the low number of data points for Series H, G, and I rounds.

5.2 Heteroscedasticity check

As in previous papers authors often confirmed the availability of heteroscedasticity, we also tested its existence. First of all, we tested its availability visually, results can be seen in Figure 7.

As can be seen in the "Residuals vs Fitted" figure there is no visual confirmation of increasing variance across the fitted values. Also, the "Scale-Location" figure does not show an increasing square root of the standardized residuals. Though to be confident we should conduct additional tests. For this purpose, we performed the Breusch-Pagan test.

Unlike graphical representations, the Breusch-Pagan test with a test statistic of 103.04 at 19 degrees of freedom clearly shows that the null hypothesis is rejected with a very high level of significance. Therefore, we can conclude that the current regression model violates the homoscedasticity assumption. Additionally, we perform a White test to be sure that heteroscedasticity exists.

White Test showed a test statistic of 108 at 38 degrees of freedom. White Test also confirms our hypothesis about heteroscedasticity, as we reject the null hypothesis with a high level of confidence. Therefore, to avoid bias and inconsistency in OLS estimators we estimated the GLS regression.

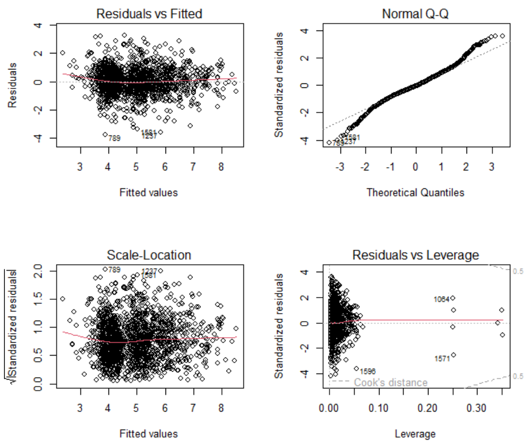

Figure 5. Residuals plot of the first regression

5.3 GLS regression

The choice of GLS regression over the common procedure of using heteroscedasticity-robust standard errors was motivated by the fact that GLS produces efficient estimators, meaning that they have the smallest variance. Such precision is important here, as we are researching financial indicators, which, if calculated incorrectly, can significantly affect investor returns in the long term.

We estimated the GLS regression with the standard procedure, by running a log-linear regression with squared residuals of the OLS residuals as the dependent variable. Then we estimated the new regression, which used exponentiated fitted values as weights. GLS regression results are presented in Table 5 below.

The difference between OLS and GLS models is not large but it exists. The variables that stayed almost the same are the impact of the age of a startup, its HQ location, and variables that were previously statistically insignificant.

Within industrial data, the absence of impact of Fintech and the AI/ML industry stayed the same. However, the impact of the Crypto industry decreased significantly. In the GLS model, Crypto startups have only a 28.8% higher valuation, while the positive effect in OLS was reaching more than 64%.

Table 5. GLS regression results

Coefficients	**Estimate**	**Std. error**	**t value**	**Pr(>|t|)**	**Significance**
(Intercept)	4.132	0.051	80.949	0.0000	***
Age	-0.069	0.006	-11.098	0.0000	***
Crypto	0.253	0.109	2.319	0.020	*
FinTech	0.030	0.066	0.452	0.651	
AI/ML	0.057	0.057	1.071	0.284	
SaaS	0.071	0.047	1.517	0.129	
a16z	0.646	0.108	5.982	0.0000	***
SoftBank	0.993	0.208	4.768	0.0000	***
Tiger Global	0.536	0.112	4.770	0.0000	***
California	0.282	0.047	6.067	0.0000	***
Texas	-0.083	0.107	-0.771	0.441	

Table 5. GLS regression results (Continued)

Coefficients	**Estimate**	**Std. error**	**t value**	**Pr(>|t|)**	**Significance**
New York	0.239	0.067	3.563	0.0003	***
Series B	1.039	0.049	21.012	0.0000	***
Series C	1.787	0.071	25.072	0.0000	***
Series D	2.181	0.115	19.033	0.0000	***
Series E	2.714	0.196	13.872	0.0000	***
Series F	2.874	0.248	11.600	0.0000	***
Series G	2.505	0.654	3.828	0.0001	***
Series H	3.647	1.187	3.073	0.002	**
Series I	2.912	0.925	3.149	0.002	**

* statistical significance at the 95% confidence level, ** 99% confidence level, *** 99.9% confidence level

Among other things, quite surprising is that the positive effect of the SaaS business model became insignificant in the GLS model, while in OLS it was significant with a 99% confidence level.

Some differences emerged within investor data. The positive effect of Andreessen Horowitz and Tiger Global Management increased only slightly. At the same time, the positive effect of SoftBank Investment Advisors increased significantly, to 169% up from 117.9% in the OLS model. This makes the impact on the valuation of SoftBank participation huge.

Some changes also happened with the impact of round variables. In general, positive effects on valuation decreased. The changes are especially large for late-stage rounds, where GLS figures for round x are close to OLS figures for round x-1.

C h a p t e r *6*

CONCLUSIONS AND RECOMMENDATIONS

This research was focused on investigating factors that affect the valuation of the startup either positively or negatively. The main factors that were assessed were the impact of the startup age, industry of operation, HQ location, business model, participation of top investors in the rounds, and the round series.

This research was inspired by previous works by foreign researchers and students from various universities, including those from the Kyiv School of Economics. This work is self-sufficient, though extends their work, as it allows the author to receive a view of the impact of factors that were not researched in previous papers.

This work is valuable for both investors and startups, as for the former it provides a view on fair valuations of the companies during their investment rounds, as well as the impact of other factors on valuation. For startups, this research may be useful when they are in the first stages of development, as it allows them to evaluate the impact of their chosen industry, business model, and geographical location on their future fundraising events.

The first factor that was studied is the age of the company, which, regarding previous works, is not surprisingly negatively affect the valuation. All other things equal, every additional year on the market decreases the valuation of the company by 7.1%. This is an aftermath of the booming 2021 VC industry, which still holds in 2022. Also, it is a sign for companies that now is a good time to start businesses, as they could easier find more funding than a couple of years ago.

Industrial data was also an important part of the research. The author distinguished Cryptocurrency, FinTech, and E-commerce industries, as they were one of the most active in terms of fundraising for several last years and are responsible for $100B+ in revenue each. However, it is worth noting that only startups that are operating in the cryptocurrency industry have higher than market valuations. Operation in FinTech and E-commerce does not have such an impact on the startup valuation. These results are rather interesting, as they show that trends have an impact on how the company is valued. Companies from industries that were in trend for several years do not have premiums to other companies, while new trends have a quite significant impact on valuation.

However, this conclusion requires additional research, which should be done with data from several periods with a clear identification of trends. Also, the research can be extended by adding new industries to it. For instance, startups that operate in alternative energy, battery technologies, or biotechnologies are such targets. Though it will require a deeper distinction of companies in terms of industries, as industry codes in the dataset are covering industries with a more generalistic and broad approach. Also, such research requires a dataset of a larger order, which is impossible with the current limitations of Pitchbook.

Building the startup with the SaaS business model did not show any positive impact on the value of the dependent variable, which is somewhat surprising. The subscription model is considered to be the most stable and crisis-resistant by venture capitalists, as it usually relies on long-term one-year or three-year contracts. Dividing companies into more business model categories can shed some light on this issue. In the author's opinion, there are two possible considerations regarding what is going on. First, the SaaS business model really does not affect the valuation of the company. Second, there exists one or a couple of other business models that receive the premium from investors and they affect the non-SaaS part of our dataset positively.

Receiving investment from strong venture investors was always a positive sign within the VC industry, which was confirmed in the research, as they usually provide startups with their network, advisory, and software services. Though we saw that there exists a difference in premiums that are offered by various investors. For instance, SoftBank Investment Advisers is offering 60%+ larger premiums compared to Andreessen Horowitz and 90%+ premiums compared to Tiger Global Management. As an extension of the current analysis, it would be interesting to enlarge the set of VC investors to find out if there exist some tiers of valuation premiums. Another possible extension of the study could be done by dividing investors geographically, into the US, European, Asian, Latin American, and others. It would be especially valuable for startups as it could provide them with a guidebook, which could ease their fundraising process by filtering more founder-friendly funds.

The geographic location of HQ also provided interesting results. California is no longer considered to be the only incorporation destination that brings value to startups. Quite a similar upside is received by the companies that are registered in New York. However, despite similar expectations for another popular destination, Texas, it has not shown similar results, as the two other states. As a recommendation, I would suggest verifying these effects for other global startup hubs, which include London, Paris, and Berlin in Europe, Singapore, Hong Kong, and Tel-Aviv in Asia, and several smaller hubs in other regions.

Another factor affecting startup valuation is the round series. The author confirmed that the company that can raise more rounds usually is more successful. Though quite interesting results for founders were received. The study revealed the magnitude of the upside that is received by any further round of fundraising. This information can be used by companies when they are planning the round valuation and the size of the round. Though further researchers can verify valuations for Pre-Seed and Seed rounds to compare them with resources that gather such data, like AngelList. Another suggestion is to study the market of M&A, where acquisition can be compared with valuations of the next round that the startup should have raised without M&A.

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