Analysis on the Blockchain Venture Industry in the United States

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Abstract. This paper provides a first look at the newly emergence of start-up firms in the U.S. blockchain industry, by documenting the gradual development of business models, technological changes, firm operations and investment behaviour of venture capitalists in this field. Drawing an analysis of the compounded annual growth rates, employment level, average revenue and valuation of 134 U.S. blockchain start-ups, this essay elaborates on the prevailing market circumstances, investment opportunities and parameters of the industry. In addition, the essay constructed several regression models replicating investment behaviours of venture capital funds and indicates that VCs would focus on long-term start-up growth and yearly revenue as parameters when funding a start-up. Furthermore, the models performed more stable when narrowed the data sample down to start-ups that received multiple rounds of VC and private equity investments, indicating the predictability and continuous growth of successful high-profile start-ups. The aforementioned models used to analyse the data sample could only be achieved by using computer analytical techniques. This paper processed the data sample using the python application, PyCharm, to perform the analysis. The overall findings are optimistic about the business, suggesting that the industry possesses high growth potential, technological progress opportunities and development vacancies for start-ups to enter the market.

Keywords: Start-ups · Venture Capital · Blockchain · Python · PyCharm

1 Introduction

The emergence of the concept of Fintech and related industries have opened new avenues of economic activities, triggered investment trends and led to a paradigm shift in the daily lives of people. Among all the epoch-making financial tools, blockchain acts as a game-changing catalyst that incentivised entrepreneurs to devote research and development in related industries and end product design. The occurrence of blockchain technology can be traced back to Nakamoto's invention of Bitcoin (BTC) in 2008, where blockchain builds the pillars of Bitcoin's decentralisation function and serves as a transparent peer-to-peer ledger recording all transactions. Cryptocurrency successors also endorsed blockchain technology as their underlying system, which now accounts for 7% of the world's money and combines $1.63 trillion worth of value. Technical studies stated that blockchain's decentralised operating system allows it to bear significant

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robustness to systematic risks (e.g., market anomalies and fraud) [1]. Fully considering the potential advantages of cryptocurrencies, blockchain technology has evolved from an underlying system of an electronic cash network to the potential operating logic of various industries, including decentralised asset management, non-fungible tokens transaction (NFTs) and smart contract execution. Correspondingly, innovative entrepreneurs who have spotted this emerging industry are launching their own start-up companies and hoping to address the first-mover advantage in the blockchain sections.

For young start-up companies whose business profiles remain blank and business model is amateur, the selection of funding among financial institutions would be narrowed down to venture capitalists, venture debt firms or angel investors. Among potential investors, venture capitalists are considered the most viable and preferable by start-up founders. Nevertheless, the investment strategies of venture capitalists differ between firms: a more significant majority of VCs are carrying out the "spray and pray" investment strategy, incorporating large sums of start-ups into the investment portfolio and waiting for individual start-ups to reach exit stages, generating promising returns to cover up the investment sum, while other VC cohorts would carry out more selective filtering of target start-ups. Such investors tend to invest based on intermediate information of the firm's operating status by implementing due diligence and regular basis information checks. This essay assumes that modern venture capitalists would carry out due diligence and start-up analysis to some extent, which builds the foundation of the following analysis. However, venture capital firms would spend less effort evaluating their target industries empirically, instead elaborating on a quantitative perspective. Multiple firm-assessing models have been proposed by scholars, including the Strength Weakness Opportunity and Threat model (SWOT) and the Competitive Forces Model, many of which are generalised models that could be adapted to any industry, which reduces its ability to spot specific investment tendencies, hence unable to make accurate investment decisions [2].

This essay spotted a new field which lacks research on providing both empirical and theoretical indications of the blockchain industry. Based on such information, this essay will analyse the blockchain industry as a whole, considering the continuous occurrence of blockchain-related start-up companies and improvements of the business models in relation to investment trends in the United States venture capital and private equity market. Furthermore, blockchain could potentially constitute a new Internet layer and trigger the next paradigm shift, contributing to high degrees of innovation and employment. Currently, smart devices are operated under the Internet protocol, whose fortunes hinge on the vast user base and scalability, generating over $1 trillion in annual value and creating countless job positions since its emergence. The remark could be drawn that the current economy operates under the Internet and related technology. Since the Internet connects nearly all the firms and individuals in the world, this essay indicates it to be an analogy for blockchain systems. The concept of Web3, proposed by one of Ethereum's designers, Gavin Wood, predicts a decentralised future of the Internet, operating under digital tokens like Bitcoin and running on a blockchain network. As Bitcoin has triggered the development of blockchain technology and the emergence of Web3 networks, new tech conglomerates in the new Web economy would be transparent, decentralised, user-contributed, and free of monopolistic power.

The concepts of the SWOT analysis, the 5-forces analysis, the hybrid business model, the product business model and the People Opportunity Context Deal (POCD) framework are reviewed and summarised in this essay to present an overall theoretical analysis of the blockchain industry. Empirical funding trends and investment model construction are explored with reference to the U.S. blockchain start-up funding information from private equity and venture capital investors from 2019 to 2021. This essay aims to evaluate the current blockchain start-up market and construct a model to generalise venture capital investment patterns with respect to various parameters of blockchain start-up operations.

The remainder of this essay is organised as follows. Section 2 summarises the past literature focused on venture capital investment trends and analytical methods of other industries. Subsequently, Sect. 3 assesses the blockchain industry from a quantitative approach. Section 4 introduces the research methodology used in the paper. Afterwards, Sect. 5 presents the results and explains their validity with performance evaluation metrics. Eventually, Sect. 6 concludes by discussing the future implications of the results.

2 Literature Review

Tracking down and analysing the investment trends and strategies of venture capital firms has been a long-term pursuit of scholars. Furthermore, relevant studies have also been carried out to evaluate specific business opportunities and start-up firms. Lastly, the new emerged concept of blockchain start-ups receives less focus in the academic field.

The few quantitative studies in this field focused on evaluating the venture capital market in a specific country or industry. By examining 24 out of 36 venture capital funds in minority businesses and studying their internal rates of return raised the conclusion that start-ups in minority businesses receive similar investment patterns compared to general mainstream businesses [3]. However, their studies only tracked down internal rates of return, the onefold research variable may contribute to an inaccurate result. To improve, this essay selected six dependent variables to evaluate a start-up from a more comprehensive scale. Kuroki (2000) targeted 220 Japanese venture capital deals and constructed a complete analysis based on financial resources, investment and business strategy, decision-making process and organisation structure [4]. Their study reflects similar caveats that the analysis is more qualitative approached, the data analysis only presents the numbers, without sufficient analysis of the data sample itself. Furthermore, this essay indicates that the start-ups chosen in Kuroki (2000) all received multiple rounds of investments, established offices in various cities and are mature market players, the results may not reflect the overall circumstance of an average Japanese start-ups.

Relevant studies focus more on qualitative research. To start with, Tyebjee and Bruno (1984) developed a five-step model that generalises the overall investment activities of venture capital firms [5]. By studying the investment decisions of 46 venture capital deals, their paper divided the funding process into deal origination, screening, evaluation, deal structuring and post-investment activities, their paper focused on the first three steps, namely spotting an attractive technology, business model or social paradigm shift, and investing in the leading start-up within this industry. Similarly, Wells (1974) and Poindexter (1976) examined 8 and 97 venture capitalists respectively, the three studies create an intersection of factors that may influence VC's investment decisions, including manager quality, growth potential, marketing plans, industry & technology and deal structuring [6, 7]. This essay regards the usage of a small data sample, namely 46 and 8 venture capital deals inaccurate, especially when such investors fund start-ups in multiple industries and sectors, the persuasion of the theoretical investment analysis lack sufficient empirical support. This essay selected a raw data sample of 897 start-ups, relevant data selection and partitioning would be elaborated in the following section.

The concept of founder backgrounds and personal capabilities also represents an important benchmark of venture capital investments. Bernstein et al. studied the behaviour of individual angel investors on the website AngelList, where they discovered crowdfunding tendency to focus on founders' background instead of other factors when deciding the investment [8]. Hochberg et al. examined the VC investment samples in the U.S. from 1980 to 2003 and highlighted the importance of founder networking and relationships in the industry [9]. A board with strong networks would likely attract more venture funding. Correspondingly, the choosing of which investor to cooperate with also relies on its networking in the VC industry and the market where the start-up operates in. Furthermore, Hellmann and Puri (2002) studied various Silicon Valley start-up funding cases and proposed their theory that venture capital investors are most likely to change original start-up board members, obtain new members and achieve efficiency maximisation [10].

Benchmarks unrelated to the firm assessment itself may also influence investment decisions. Hechavarría et al. (2016) proposed that deal structuring is also a critical factor that alters VC preference for investment actions [11]. They argue that the initial financial structure chosen by a start-up plays an essential role in attracting follow-up ventures, accelerating start-up growth and pushing the investment to an exit phase. Ning et al. (2015) studied venture investment deals from 1995 to 2011 and concluded the importance of macroeconomic indicators and market factors [12]. Their studies examined the positive impacts of growing real GDP, greater industry production indices and lower unemployment rates on average deal investment and the total number of start-up deals. In addition, Ewens et al. (2017) researched the impact of technological shocks on start-up financing, where they drew a connection between the initial cost of production and technical status and hence concluded that overall technology progress would incentivise investors to implement different funding strategies, namely the spray and pray strategy [13].

This essay highlights the POCD framework proposed by Sahlman (1996) as a more generalised evaluation metric for specific businesses and industries [14]. The framework comprises four counterparts: people, opportunity, context, and deal. It is worth noting that all four factors are reflected in the previous literature analysis, where people represent the ability, capability, and networks of the founding members; opportunity represents the market structure, competition, technological advancement and target consumer base; context represents the macroeconomic environment and deal represents the capital structure, financing tools and ownership allocation. This essay's focus is an overall evaluation of the blockchain industry. Therefore, the qualitative approach lies mainly in the opportunity and context analysis.

Few scholars have evaluated the blockchain start-up industry, which of fewer have conducted research from a quantitative approach. Yan and Bellavitis (2019) concluded that the nouveau blockchain technology could reduce transaction costs, support peer-to-peer transactions and trigger a paradigm shift in decentralised financial models [15]. Therefore, they predict that future blockchain industry would experience a rapid growth in start-up establishment.

The blockchain industry includes the provision of final goods and services related to the core blockchain technology, new applications, services and business initiatives have been established on a daily basis, where the most important sub-markets included the management of decentralised crypto assets, NFT trading and digital smart contract invention. The global blockchain industry is categorised into various sectors. The foundation sector consists of peer-to-peer blockchain networks, involving transactions over decentralised platforms, such services are mainly presented as trading of cryptocurrencies such as Bitcoin and other online exchange platforms. The second sector incorporates the trading of digital assets, where digital tokens are issued, purchased and transferred via a blockchain network, unlike crypto assets, such services mainly trade end products such as NFTs. The third sector is the market for applications, services, and supporting infrastructure, some companies may be established before emergence of the blockchain technology but incorporated it into their operating system or business model, when pursuing this goal, such firms may hire blockchain start-ups to construct, assemble and activate the blockchain system of such firms.

Based on Yan and Bellavitis (2019)'s conclusion and the POCD framework, the blockchain market possesses high growth potential and a large target consumer group [15]. The third sector mentioned above could enable any established firm to become target customers, blockchain start-ups that act as service providers could benefit the most by incorporating their blockchain systems into the current financial system. Furthermore, the rise of the Web 3 era and the development of decentralised financial systems may give rise to a paradigm shift in the current socio-economic network, implying blockchain to be an underlying driving system of financial transactions and digital payments in the future, therefore, the industry possesses a strong potential to grow. Therefore, the following passage will evaluate established blockchain start-ups, analyse the current start-up market and models venture capital investments and blockchain start-up growth.

3 Quantitative Industry Analysis

3.1 Data Selection

The data sample used in this essay is selected from the private company financial database, PrivCo. The website covers all relevant data of start-ups, including earnings before interest, taxation and amortization (EBITA), yearly revenues, employee growth valuation and funding details. This essay selected 897 start-ups across three industries, the blockchain industry, the NFT industry and the decentralised assets and cryptocurrency industry. Among these start-ups, this essay filtered the companies without three years of revenue growth, any rounds of investment or claimed bankruptcy, since these

Table 1. Descriptive data of blockchain start-up data set.

	Mean	SD	Min	25-th	50-th	75-th	Max
1 Year Revenue Growth	181.40	566.50	-1.20	8.57	20.43	100.00	4233
3 Year Revenue Growth	34.59	38.03	-13.38	9.14	21.63	47.54	171.4
1 Year Employee Growth	36.60	70.79	-14.30	4.40	10.80	36.40	400.0
3 Year Employee Growth	30.25	40.14	-13.40	5.95	15.90	41.90	171.4
Average Revenue (billion)	0.20	0.94	0.00004193	0.011	0.02	0.046	7.90
Valuation (billion)	2.70	11	0.0015	0.048	0.25	1.50	120

firms are considered either losing entities during competition with other cohorts or situated in their primary phases. After the filtering, this essay targeted 134 start-ups, including 82 blockchain start-ups, 5 NFT firms and 47 cryptocurrency companies. Within the 134 start-ups, all companies have received more than two rounds of investment and an average firm received 3.84 rounds of funding, while 45 start-ups have received private equity investment and 106 firms have received venture capital investments.

In the regression analysis, the data sample is adjusted into two samples, one sample contains 106 observations that have been invested by venture capital funds for at least one round of funding, and another sample consists of 26 start-ups that are both funded by venture capital and private equity funds. The 26 firms listed are considered to be more mature in their industries and reaching a further funding phase, which narrows down the analysis result to a target of advanced and high-profile start-ups in the blockchain industry.

The following Table 1. lists the basic descriptive data of the sample statistics. It is exhibited that the yearly growth of these firms, which is calculated from the percentage growth of the compound annual growth rate (CAGR), gradually slows down by comparing the average revenue growth of 181.4% in one year and 34.59% in three years. In addition, the blockchain industry presents a large deviation between growth in high-potential start-ups and the lowest 25% quartile, both reflected in a higher one-year growth rate (100% to 8.57%) and their three-year growth rates (47.54% to 9.14%). Furthermore, the annual employment growth rates present similar trends as the revenue growth, high profile start-ups would improve their personnel allocation and possess more resources to achieve increased employment. However, it is worth noting that start-up firms may not hire many employees and such firms should not be regarded as a significant contributor to stable and sufficient job vacancies. The last two sections present descriptive data on the average revenue and valuation of blockchain start-ups. The average revenue is calculated by taking the mean revenue from 2019 to 2021, in order to fully reflect the potential influences of the Covid-19 pandemic. The average revenue earned by the industry is \$200 million, while average valuations reached up to \$2.7 billion. Some specific companies such as Stripe, Inc., Kraken and Citadel Securities, LLC. Generated high annual revenues and contribute significantly to the high average revenue and firm valuation. Notwithstanding, these unicorn businesses and large start-up leaders provide a positive effect on leading the market and attracting more entrepreneurship to the industry.

3.2 Model Selection

To start with, this paper applies the Pearson product-moment correlation coefficient (PPMCC) to measure the correlation between the variables presented in the dataset. Let two random variables, X, Y with expected values μX and μY and standard deviations s(X) and s(Y). The correlation coefficient Corr (X, Y) is defined as:

$$corr(X, Y) = \frac{cov(X, Y)}{\sigma(X)\sigma(Y)} = \frac{E[(X - \mu X)(Y - \mu Y)]}{\sigma(X)\sigma(Y)} \tag{1}$$

where Cov (X, Y) is the covariance between X and Y, E means the expected value. The range of correlation coefficients varies from -1 to 1. It is defined that two variables imply a strong correlation relationship if the absolute value of the coefficient is bigger than 0.7, a weak correlation between 0.3 and 0.7, and no correlation if the value is less than 0.3.

The regression model selected in this essay is the Least Squares Regression (OLS): Known as the linear regression model, the equation of the OLS model is presented as follows:

$$Y = \beta_0 + \sum_{j=1}^{p} \beta_j X_j + \varepsilon \tag{2}$$

where Y is the dependent variable, β0 is the segment of the model, Xj is the jth explanatory variable of the model (j = 1 to p), and ε is the error of the probability error model due to the expected value 0 and the variance σ2.

Three performance metrics were used to assess the regression results and compare the accuracy of different methodologies on investment relationship derivation: R-square adjusted R-square and Mean Square Error (MSE). The elaboration of the three metrics is as follows:

R-square: R-square is the square root of the correlation coefficient (R) and measures how the model explains the variability in dependent variables. The value of R-square lies between 0 to 1, and a higher value represents a better fit for the model. To evaluate, however, R-square does not consider the over-fitting problem, in which, in some cases, the result is over-estimated. The R-square formula is elaborated as follows:

$$R^2 = 1 - \frac{SS_{Regression}}{SS_{Total}} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \overline{y})^2} \tag{3}$$

Adjusted R-square: Similar to the R2, adjusted R2 measures the percentage of variance in the targeted field explained by its inputs and outputs while reducing the possibility of the over-fitting problem that the R2 model exhibits. The equation is shown as follows:

$$Adjusted\ R^2 = 1 - \frac{(1 - R^2) \times (N - 1)}{N - p - 1} \tag{4}$$

where N is the total sample size and p is the number of independent variables.

MSE: Mean Squared Error calculates the average goodness of fit for the regression model. This value is calculated by deducting the predicted and actual value difference, divided by the number of data inputs and taking the average squared difference. The closer the value of MSE is to 0, the less the predicted value deviates from the actual value, and the better the regression model is. The MSE formula is elaborated as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 \tag{5}$$

where N is the number of data points, Yi is the measured value and $\widehat{\mathrm{Y}}_{\mathrm{i}}$ is the predicted value.

The aforementioned models used to analyse the data sample could be efficiently achieved by using computer analytical techniques. This paper processed the data sample using the python application, PyCharm, through the steps of data processing, model construction and regression analysis.

3.3 Data Sample Analysis

This section starts the analysis by elaborating on the correlation between different factors regarding start-up funding. The factors selected are listed in the previous descriptive data table, which includes one and three-year revenue growth rate (CAGR rate), one and three-year employee growth rate, average revenue from 2019 to 2021 and the current company valuation. Table 2. listed the correlation coefficients with a more straightforward approach.

The most obvious observation derived from the table is the strong correlation between average annual revenue and company valuation. The strong correlation of 0.824 follows the investment rules of venture capitalists that only start-ups with high earnings and annual revenue would address real corporate value. However, the compounded annual growth rates, both for one year and three years exhibit no correlation with the valuation

Table 2. Correlation table of chosen factors for blockchain start-ups.

	1 Year Revenue	3 Year Revenue	1 Year Employee	3 Year Employee	Average Revenue	Valuation
1 Year Revenue	1					
3 Year Revenue	0.373	1				
1 Year Employee	0.472	0.35	1			
3 Year Employee	0.337	1	0.406	1		
Average Revenue	−0.017	0.009	-0.005	0.111	1	
Valuation	0.043	0.081	0.044	0.104	0.824	1

of a start-up, the correlation coefficients are only 0.043 and 0.081 respectively. It could be explained that since the real amount of revenue and the growth rate are not linked directly, namely the smaller a start-up is the most likely it could address high growth rates, yet for high-potential and successful start-ups that possess larger market shares, achieving high growth rates would be more difficult.

The relationship between one-year employee growth and one-year revenue growth presents a weak positive correlation of 0.47. For some start-ups, a cash flow approaching the break-even level and increasing revenue reflects a healthy status, thus, could support them to hire more staff and employ higher quality factors of production. Nevertheless, most start-ups are not yet reaching an inflexion point on their cash-flow cycle, even if revenue is positive and market potential remains optimistic, founders and investors would not prefer to assemble a mature and advanced human resource centre such early, instead relying on the founding members and receiving advice from investors. Furthermore, the 0.46 relation between one and three-year employee growth exhibits a weak positive correlation. It could be derived that start-ups that do well in their first year would potentially maintain the momentum and keep improving the quantity and quality of employees hired. However, this essay filtered down most start-ups without a three-year growth rate, under the potential survivorship biased result, the correlation may be lower after incorporating all 800 start-ups since most of them may dismiss or go bankrupt within three years of operation.

This essay also developed a regression analysis between different variables in a start-up's operations. The factors of total funding and company valuation are processed as controlled variables. The independent variables in this model are start-up valuation, total funding amount, and whether or not backed by venture capital or private equity, while the dependent variables were chosen are one and three-year CAGR rates, one and three-year employee growth rates and average revenue. The regression coefficient results of the first data sample consisting of 106 observations are presented in Table 3.

To evaluate the performance of this model, the following Table 4. presents the results after processing through the performance metrics, the values of R2, adjusted R2 and mean square error are shown. The R2 values, both adjusted and un-adjusted for the first four independent variables exhibit a weak relationship between the model and the regression results, while the average annual revenue model presents a value of approximately 0.52.

Table 3. Regression coefficients of blockchain start-up industry (without filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Valuation	97.892*	8.691**	1.778	8.691**	0.530***
Total Funding	−20.554	−6.01	6.377	−6.01	0.019
PEB	−124.667	19.220**		19.220**	−0.544**
VCB	84.077	1.299		1.299	−0.359
Constant	−1,388.593*	-37.826	−105.917	−37.826	6.700***

Table 4. Performance metric test of blockchain start-up industry (without filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Observations	106				
R-squared	0.089	0.225	0.055	0.225	0.522
R2_adjust	0.0524	0.173	0.0233	0.173	0.504
MSE	607.75	29.927	77.731	29.927	1.1342

The R2 value of 50% in this context, could be considered as a well-fit model since there exists many unqiue factors in venture capital investments and a 50% possibility of fitting the model indicates an apt prediction. Whereas the MSE value implies a relatively unstable characteristic within the models. The MSE metric calculates the errors present in a regression model by giving all errors the same weights; the goal of an ideal model is an MSE value of 0, which exactly fits the actual trend. The MSE value of the five regressions deviates significantly. The 607.75 MSE value of the 1 Year CAGR regression indicates a great extent of exposure to risks and volatility in the prediction phase, that the predictive value deviates significantly from the actual value. Even though regression models are proven to fit the actual value most of the time, these models are still amateur in speculating target start-ups by predicting future performances. However, the small MSE value of 1.13 for the average revenue model proposed a significant possibility that the prediction is correct.

The following Table 5. presents the null-hypothesis significance testing of the regression results. The significance parameter is set as t-statistics in parentheses $p < 0.01$ indicates generalisation ability less than 1%, $p < 0.05$ indicates generalisation ability less than 5%, and $p < 0.1$ indicates generalisation ability less than 10%. The significance test shows how well the regression could be generalised into a wider range of datasets and sample statistics, whereas a small significance value indicates the model to be overfitting and unable to generalise results to further research. The results of significance testing present similar results as the previous analysis. It is worth noting that two models, constructing the total funding relationship and the venture capital investment model exhibit high generalisation abilities with a significance of 0.519 and 0.798, respectively.

The results of bivariate filtering will be presented in the following passage, where start-ups which received both venture capital and private equity investments are filtered, and 26 observations were made. The independent and dependent variables are unchanged in this context yet the focus of the data sample is narrowed down to a specific sector of the blockchain industry, namely the more developed and high-potential start-ups. The regression results are presented in the following Table 6.

The regression results were processed through the evaluation metrics and values are shown in the following Table 7. Within 26 observation results, the average revenue variable still exhibits a better performance in R2, adjusted R2 and MSE values, of 0.765, 0.72 and 0.94, respectively. This pattern reflects an overall accurate regression fit and low occurrence possibilities of disruptive circumstances. Nevertheless, the overall

Table 5. Significance test of blockchain start-up industry (without filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Valuation	0.081	0.029	0.82	0.029	0
Total Funding	0.78	0.251	0.424	0.251	0.891
PEB	0.363	0.026		0.026	0.035
VCB	0.782	0.942		0.942	0.527
Constant	0.016	0.293	0.216	0.293	0

Table 6. Regression coefficients of blockchain start-up industry (with filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Valuation	56.627**	11.148	8.075	11.148	0.661***
Total Funding	−37.595	−6.591	−3.98	−6.591	−0.029
PEB	11.453	22.769	14.38	22.769	−0.944**
VCB	65.368	−13.426	10.555	−13.426	0.304
Constant	−424.438*	-65.933	−76.853	−65.933	5.091***

Table 7. Performance metric test of blockchain start-up industry (with filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Observations	26				
R-squared	0.365	0.311	0.263	0.311	0.765
R2_adjust	0.245	0.18	0.123	0.18	0.72
MSE	113.3	34.074	31.221	34.074	0.94106

performance of all variables improved after narrowing down the sample set, represented in the values of all three performance metrics.

The significance test with bilateral filtering is presented in Table 8., it follows similar benchmarks, the average generalisation capabilities of the regression models improved and indicates the narrowed dataset could be more specific in order to serve future predictions of start-ups. Notwithstanding, the total funding, private equity and venture

Table 8. Significance test of blockchain start-up industry (with filtering).

	1 Year CAGR	3 Year CAGR	1 Year Employee Growth	3 Year Employee Growth	Average Revenue
Valuation	0.041	0.169	0.273	0.169	0.006
Total Funding	0.267	0.514	0.666	0.514	0.917
PEB	0.831	0.167	0.335	0.167	0.043
VCB	0.495	0.64	0.688	0.64	0.702
Constant	0.036	0.26	0.156	0.26	0.004

capital functions all exhibit high significance patterns, consistent with the result without bivariate filtering.

4 Conclusion

By analysing the current blockchain start-up market, this essay spotted that various unicorns and high-profile companies possess significant market shares, yet the growth potential of the overall blockchain market remains vacant and could empower the larger inclusion of blockchain start-ups. This essay also constructs regression models that interpret investment decisions of venture capital and private equity funds, tending to propose a pattern between start-up valuation and operation parameters. The regression results imply that the average revenue and three-year compounded annual growth rate remain as two significant indicators of start-up performance. In addition, when narrowed down to advanced and well-developed start-ups that received multiple funding rounds from both private equity and venture capital investors, the performance of regression results, tends to improve, which indicates a more stable and predictable operating status as a blockchain start-up reaches a mature phase of development. Even though numerous challenges still need to be addressed, entrepreneurs and innovators have been experimenting with decentralized business models that are traditionally not viable without blockchain technology. This essay indicates that the successful incorporation of decentralised business models could increase blockchain start-up growth. Moreover, the gradual development of the blockchain industry could create a new field of research and affect the operation of the financial market as a whole.

References

1. Drescher. Blockchain Basics: A Non-Technical Introduction in 25 Steps (1st ed.). Apress. 2017.
2. Porter. Competitive Strategy: Techniques for Analysing Industries and Competitors. New York, Free Press, 1980.
3. Bradford, and T. Bates. Venture Capital Investment in Minority Business. SSRN Electronic Journal, vol. 40, 2005, https://doi.org/10.2139/ssrn.796406. Accessed 9 Aug. 2020. p489–504.

4. Kuroki, et al. Emerging Trends in the Japanese Venture Capital Industry. The Journal of Private Equity, vol. 4, no. 1, 30 Nov. 2000, pp. 39–49, https://doi.org/10.3905/jpe.2000.319976. Accessed 12 June 2022.
5. Tyebjee, and A.V. Bruno. A Model of Venture Capitalist Investment Activity. Management Science, vol. 30, no. 9, Sept. 1984, pp. 1051–1066, https://doi.org/10.1287/mnsc.30.9.1051.
6. Wells. Venture Capital Decision Making. unpublished doctoral dissertation, Carnegie-Mellon University, 1974.
7. Poindexter. The Efficiency of Financial Markets: The Venture Capital Case. unpublished doctoral dissertation, New York University, New York, 1976.
8. Bernstein, et al. Attracting Early Stage Investors: Evidence from a Randomized Field Experiment. SSRN Electronic Journal, 2014, https://doi.org/10.2139/ssrn.2432044. Accessed 3 Sept. 2019.
9. Hochberg, et al. Whom You Know Matters: Venture Capital Networks and Investment Performance. The Journal of Finance, vol. 62, no. 1, 11 Jan. 2007, pp. 251–301, https://doi.org/10.1111/j.1540-6261.2007.01207.x.
10. Hellmann, and M. Puri. Venture Capital and the Professionalization of Start-up Firms: Empirical Evidence. The Journal of Finance, vol. 57, no. 1, Feb. 2002, pp. 169–197, onlinelibrary.wiley.com/doi/https://doi.org/10.1111/1540-6261.00419.
11. Hechavarría, et al. Does Start-up Financing Influence Start-up Speed? Evidence from the Panel Study of Entrepreneurial Dynamics. Small Business Economics, vol. 46, no. 1, 10 Oct. 2015, pp. 137–167.
12. Ning, et al. The Driving Forces of Venture Capital Investments. Small Business Economics, vol. 44, no. 2, 22 June 2014, pp. 315–344, https://doi.org/10.1007/s11187-014-9591-3. Accessed 14 Aug. 2020.
13. Ewens, et al. Cost of Experimentation and the Evolution of Venture Capital. SSRN Electronic Journal, no. 15–070, 2015.
14. Sahlman. Some Thoughts on Business Plans. Harvard Business School, vol. 9–897–101, 14 Nov. 1996.
15. Chen, and C. Bellavitis. Blockchain Disruption and Decentralized Finance: The Rise of Decentralized Business Models. SSRN Electronic Journal, 2019.