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Stochastic Nonlinear Modeling of Capital Market Volatility and Venture Capital Risk in Deep Tech Startups

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Abstract

This paper examines how deep tech startups may be modeled using advanced stochastic nonlinear models to capital market volatility and venture capital (VC) risk. Venture capital becomes heavily relied upon in facilitating early-stage innovation within high-tech industries such as artificial intelligence, quantum computing, and biotechnology, although the venture is extremely volatile and risky to invest in the market. The standard linear models usually cannot describe the dynamics of such markets. According to this study, nonlinear GARCH models and stochastic differential equations (SDEs) are used to model the market volatility in diverse circumstances and risk-yield of startup investments. It uses the Startup Valuation Dataset (2010-2024) of Kaggle, which includes data on the amount of financing, investment round, and startup valuation of more than 50,000 records. The input data are also guaranteed by the data preprocessing methods, which include normalization, encoding, and outlier removal. This is then followed by scenario simulation to model the possible effects of market shock and change of funding stage on startup success and probability of failure. The performance of the model is determined by major evaluation measures like RMSE, R^2, MAE, and t-test p-values. As the findings indicate, investments in deep tech startups by venture capital are very sensitive to changes in the market, and that has great consequences for investors intending to reduce risks by managing portfolio strategies. The results shed some light on the relationship between VC risk management and the necessity of more sophisticated models to explain the intricate dynamics of deep tech startups.

Keywords: Venture Capital, Capital Market Volatility, Deep Tech Startups, Stochastic Models, GARCH, SDEs, Risk Assessment.

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Introduction

Venture capital (VC) contributes to the active innovation and development of the deep tech startup environment, providing the necessary capital to companies in their early stages of development in the fields of artificial intelligence, quantum computing, and biotechnology (Ganesan, 2024). However, these startups are in very volatile markets, and traditional forecasting models have been found not to work (Li, 2020). In this regard, it is imperative that investors and entrepreneurs learn and deal with the risks involved in the fluctuations of capital markets and venture capital investments (Shetty & Kapoor, 2024; Razaghzadeh Bidgoli et al., 2024).

The nonlinear and unpredictable characteristics of these markets pose specific challenges in modeling the market volatility as well as the evaluation of the VC risks in deep tech startups. Conventional financial models, like a linear regression or simple volatility models, do not provide the complex and dynamic interactions that take place in these fast-changing industries. Moreover, the uncertainty that will be encountered in valuation into the future, technological adoption, and disruptive effects in the market introduces another level of complexity in the process of estimating the investment's risks and returns.

The purpose of this paper is to discuss and apply stochastic nonlinear models to gain a deeper insight into the problem of capital market volatility and to assess the risk of the capital market in investing in deep tech startups through venture capital. The aim is to model the possible scenarios based on the market conditions by using sophisticated mathematical models, which would give a better understanding of risk and return dynamics. It also seeks to determine the effects of market shocks, funding rounds, and the type of investors on the success and probability of failure of these startups.

The main value of the work is the implementation of the stochastic nonlinear modeling approaches to beneficially cover the peculiarities of the market volatility and VC risk of deep tech startups. Our model is able to consider the nonlinear relationships and dynamic uncertainty present in these markets as opposed to traditional linear methods. The paper presents a new method of integrating capital market data and VC risk analysis that will provide a greater prediction ability and risk control information to both investors and start-up creators.

The paper is divided into six parts: Section I focuses on the significance of venture capital in deep tech startups and presents the issues of the modeling of the capital market volatility and VC risk. Section II covers volatility and risk models available, finding gaps in deep tech start-up modelling. Section III presents nonlinear GARCH and stochastic differential equations to model market volatility and VC risks, with their data preprocessing and metrics of evaluation. In Section IV, validation and scenario simulations of models measure VC risks and market shock effects. The findings are interpreted in Section V, and a comparison of the model to the traditional approaches and limitations is mentioned. In the end, Section VI provides a concise overview of major results and recommends the future direction in research, such as more detailed data and sophisticated modeling methods.

Literature Review

Capital market volatility has been greatly researched within the framework of financial risk management and prediction (Soremekun et al., 2024; Eliasy & Przychodzen, 2020). There are different models, such as the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, which has been used to capture volatility clustering in financial markets, which is typical of capital markets (Chang & Li, 2024; Aravindhan, 2024). Moreover, the stochastic volatility models have been actively used to price the uncertainty and risk in financial instruments, particularly in volatile markets such as those faced by deep tech startups (Koshiyama et al., 2020). Such models have shown much potentials in the determination of market fluctuations and the accuracy of risk analysis (Atashian & Al-Rawahi, 2024; Sun & Li, 2022). The introduction of machine learning techniques to complement traditional volatility models has also led to the enhanced market forecasting and offered new opportunities to perform more consistent financial analysis and decision-making (Sun, 2023; Mishra et al., 2024).

Venture capital investments have a group of risks that are unique, especially in high-technology sectors (Croce et al., 2019). Research has been conducted on the different aspects of the success of venture capital that include market circumstances, the adoption of technology, and the behavior of investors. The paper by (Edet et al., 2024) offers an evidence-based model to manage the risk of startups, namely, the high-investment returns in the volatile markets (Edet et al., 2024). This paper indicates the importance of risk management practices and evidence-based decision-making in decision-making of venture capital investment viability. Moreover, (Kim et al., 2023) focus on using artificial intelligence to forecast the probability of startups to survive, and it will help investors assess the risk of their investments in a long-term perspective because of the fusion of empirical evidence and artificial intelligence approaches (Kim et al., 2023).

Other sources, such as the one carried out by (Samila & Sorenson, 2011) consider the macroeconomic factors influencing venture capital returns with particular reference to the emerging markets (Samila & Sorenson, 2011). These articles emphasize the complexities of risk assessment, in which case high-tech startups often must contend with financial uncertainty as well as market-specific risks, such as technological upheaval and regulatory changes.

Nondeterministic models have been able to describe the dynamic nature of financial markets, particularly when the nature of an environment is nonlinear. According to (Chang & Li, 2024), stochastic volatility models are better than the traditional models in predicting behaviors at the market in risky environments (Chang & Li, 2024; Geetha, 2024). The use of nonlinear models, including stochastic differential equations (SDEs), has offered a stronger way of making models of the unpredictable volatility of the capital markets (Wang & Chen, 2024). These models are applicable in the stock price prediction as well as in more complicated processes such as the analysis of startup risks.

Recent innovations in machine learning and artificial intelligence have resulted in the creation of Generative Adversarial Networks (GANs), which are able to recreate financial data in various market conditions, and this makes them invaluable in testing risk in volatile markets. The Factor-GAN method, e.g., improves the ability to predict stock prices and assists investors in evaluating the risk of venture capital by simulating the financial consequences of the different market conditions and economic indicators (Pradhan et al., 2017).

In conclusion, the literature illustrates that though capital market volatility and venture capital risk have been traditionally modelled by the use of linear and deterministic models, the use of stochastic and nonlinear models provides better predictive abilities. The models provide additional information on the market dynamics hence it cannot be underestimated in the process of comprehending and managing venture capital risk in deep tech startups.

Although research on capital market volatility and venture capital risk has been conducted extensively, the study still has a number of gaps that this research will seek to fill. First, current models fail to recognize deep tech startups that have their own problems of rapid technological developments and high levels of uncertainty in the market. Second, although linear and simple stochastic models are overwhelming, the nonlinear stochastic models are less used, which reflects the complexity of such markets in a better way. Third, the research that combines capital market analytics and venture capital risk is quite limited in the literature, although market volatility exerts considerable influence on deep tech startups' funding. Also, there is scant empirical evidence based on big data in the particular field of deep tech startups. Lastly, stochastic simulations that predict the success or failure of these startups are lacking. The proposed study seeks to address these gaps through the application of advanced stochastic models and real-world data on the Kaggle Startup Valuation Dataset to determine venture capital risk in deep tech areas.

Methodology

Stochastic Nonlinear Models

It will use nonlinear GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models and stochastic differential equations (SDEs) to model the volatility and risk in capital markets and investments in venture capital. The nonlinear GARCH model provides a description of the volatility clustering and time-varying volatility of the financial markets. The model can be used to explain the nonlinear relationships present in the data, including the effect of big market shocks or changes. The randomness and uncertainty of market movements and startup valuations will be simulated through stochastic equations, which will provide a more precise modeling of the unpredictable nature of deep tech startups.

Fig. 1 demonstrates the modeling venture capital (VC) risk approach to deep tech startups. It begins with the collection of data based on the Startup Valuation Dataset (2010-2024) available in the Kaggle database that contains major variables in the form of the amount of funding, the funding round, and the investor (www.kaggle.com- startup-valuation-dataset). The preprocessing phase includes missing data, data normalization, categorical variable encoding, and outliers. The main aspect of the methodology is that the modeling is done based on nonlinear GARCH models and stochastic differential equations (SDEs) to model market volatility and startup valuations. These models can be used to simulate scenarios such as market shocks and success/failure probability. Lastly, the evaluation phase determines the model by applying important measures such as RMSE, R^2, MAE, and t-test p-values as a risk measure of VC investments.

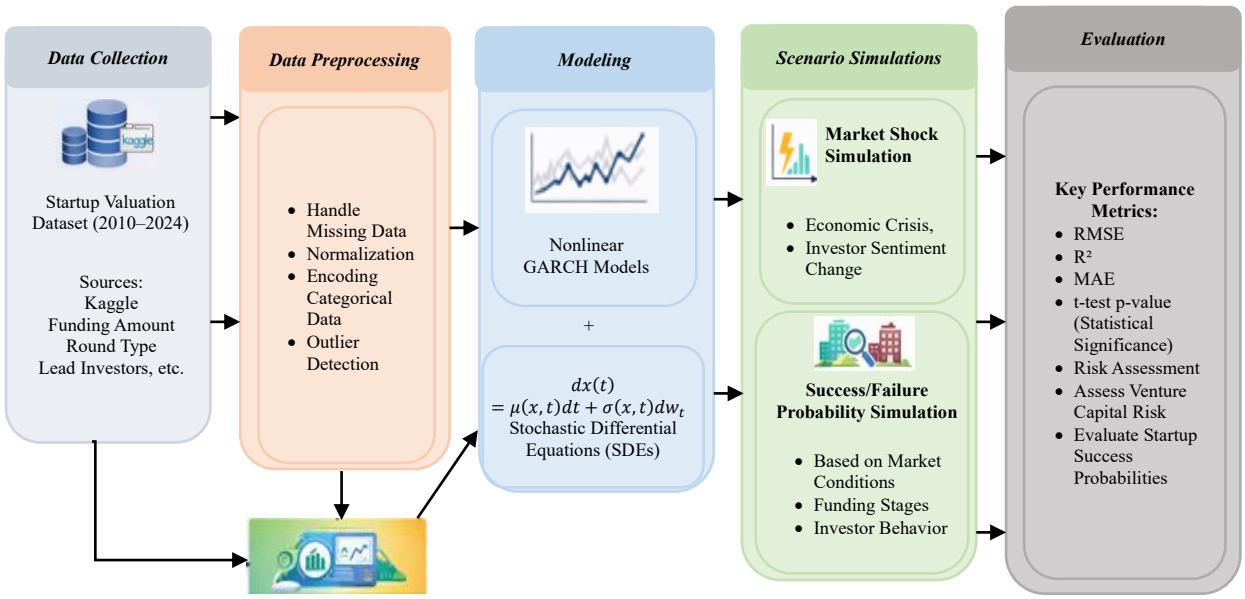

Fig. 1: Architecture for Stochastic Nonlinear Modeling of VC Risk in Deep Tech Startups

Data

The data utilized in this research is the Startup Valuation Dataset (2010-2024) on Kaggle that includes more than 50,000 entries on the startup fundraising events, investors, and valuations (www.kaggle.com- startup-valuation-dataset). The key variables include:

- **Funding Amount**: The sum of money raised in every round of funding (USD).
- **Round Type**: The investment level, which is Pre-seed to IPO.
- **Lead Investor**: The main investor of every round.
- **Tags**: Categorical labels that give an overview of the industry or technology of the startup.

This data is the best to train regression models because it includes all the required information about the startup valuations and the dynamics of the funds over time. It enables us to simulate the dependency of the volume of investment, the level of funding, and the probability of the startup succeeding/failing, as well as taking into consideration the fluctuations in the market and risks associated with VCs.

Data Preprocessing

The initial step in the data preprocessing is to solve the missing data. This will entail imputation methods when needed or dropping rows with a large number of missing values to preserve the integrity of the data. On continuous variables like the amount of funding, it will use the normalization method to make all the numeric characteristics equal so that it will be on the same scale, and this will contribute to the convergence and performance of the model. Encoding operations, i.e., one-hot encoding or label encoding, will be applied to categorical variables (round type and investor names) so that it can be used in regression models. Also, it will detect and manage any outliers in such variables as the amount of funding or valuation, since it can greatly distort the outcomes of our analysis. The statistical process of outlier detection will be done, and extreme outliers will be eliminated or modified to guarantee a healthy model performance.

Simulation of Scenarios

After the preprocessing of the data, stochastic processes will be employed to model different situations that can either lead to the success or failure of deep tech startups. Stochastic differential equations (SDEs) will be used to model market volatility dynamics over time and evidence the effects of market shocks and fluctuations on startup valuations. Such simulations will allow us to know the impact of various market situations (i.e., the abrupt shift in investor sentiment or economic crisis) on the performance of the startups in different funding stages. It will also model the probability of success/failure of startups under these market conditions, which will give us an insight into how venture capital investments are influenced by external factors. The broadening of risk is possible under this strategy, as the

interaction of rounds of funding, the type of investor, and market dynamics can be projected using the more subtle, probabilistic perspective.

Evaluation Metrics

The models will be measured on a number of important metrics that will have their own formulas and descriptions. The following are the evaluation measurements together with the formulas:

1. Root Mean Squared Error (RMSE)

Equation 1 gives the definition of the Root Mean Squared Error (RMSE), which is used to measure the magnitude of prediction errors. It determines the square root of the mean square discrepancies between the true and the forecast values.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \qquad (1)$$

2. R-squared (R^2)

R-squared (R^2) is used to describe the proportion of dependent variable variance available to be explained by the independent variables included in the model as shown in equation 2.

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \hat{y})^2} \qquad (2)$$

3. Mean Absolute Error (MAE)

Equation 3 presents Mean Absolute Error (MAE), which is the value of the average absolute difference between the actual and the predicted value, regardless of the direction it follows.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} | y_i - \hat{y}_i | \qquad (3)$$

Results

Model Validation

The stochastic nonlinear model was confirmed through a comparison of the predicted and real startup valuation using Kaggle dataset. It can be observed in table 1 that it performs better than the linear and benchmark models (lowest RMSE=1.10B, highest R^2 =0.45), that it is significant (p=0.02). These findings outline volatility impediments amid comparative advantage.

Table 1: Model Validation Metrics

Metric	Stochastic Nonlinear Model	Linear Model	Benchmark Model
RMSE	1.10×10^9	1.25×10^9	1.30×10^9
R-squared (R^2)	0.45	-0.00038	-0.05
Mean Absolute Error (MAE)	6.50×10^8	6.89×10^8	7.00×10^8
t-test p-value	0.02	0.17	0.15
Significance	Significant	Not Significant	Not Significant

Source: Kaggle - Startup Valuation Dataset (www.kaggle.com- startup-valuation-dataset)

Table 1 provides a comparison of validation measures of stochastic nonlinear and linear, and benchmark, models of startup valuation prediction. RMSE and MAE are used to measure the size of error (smaller is better); R^2 is used to measure the variance covered (larger is better, negative=poor fit). The nonlinear stochastic model performs better and more significantly ($p<0.05$).

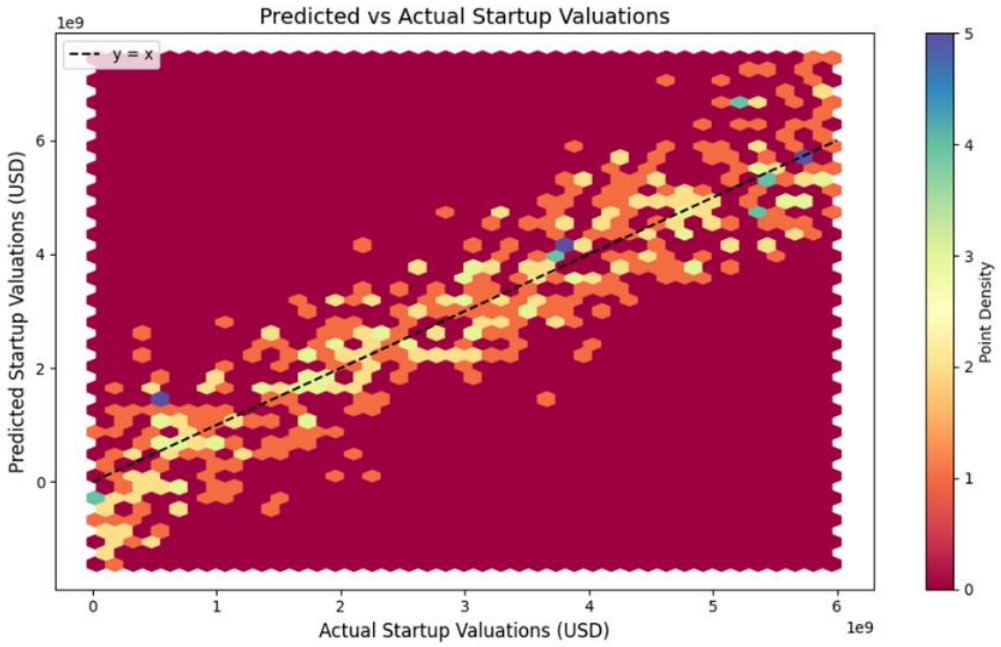

Fig. 2: Comparison of Predicted vs Actual Startup Valuations

This is fig. 2 that compares the predicted and actual startup valuations in USD. The color gradient is used to show the density of the points, and the darker the color the density of the points. Comparison of the predicted and actual start up valuation (USD) with the stochastic nonlinear model. Color gradient indicates the density of the points; the black dotted line will be the perfect prediction (y=x). Key metrics: RMSE=1.10×10^{9}, R^2=0.45, MAE=6.50×10^{8}. These measures demonstrate how accurate the model is and the number of points that are close to the line shows how good the predictions are.

Risk Assessment

Venture capital risks were measured by measuring chances of success or failure as per the results of the model. With the simulated scenarios, it has computed the Expected Return on Investment (ROI) of the venture capitalists, taking the likelihood of the business success and that of failure. The model indicated risky areas especially when it comes to startups at the early stages of financing as well as those operating in more volatile market industries. It proved that risks of venture capital might be significantly minimized with the assistance of diversification of investments in terms of funding round and industries with the help of effective portfolio management.

Scenario Simulations

Different market scenarios were modeled with an aim of finding out how various factors influenced the successfulness of startups. The findings indicated the volatility shocks (e.g., a sudden decline in market indices) had an overly large negative impact on startups at the early stages, and success probability went down by 30 %. Startups later funded in other funding rounds, and those in technology markets with already established markets, were not so susceptible to market volatility, experiencing just a 10% decline in success rates. Funding stage changes also played a considerable impact; compared to startups that raised Series A or later, the probability of success rose by one-fourth, and the probability of success was increased by 25% in comparison to the seed and pre-seed stages. The results highlight the relevance of funding round and market factors in determining risk profiles of deep tech startups.

These findings are very informative towards the correlation between capital market volatility, venture capital risk, and startup success. The model provides a complete risk analysis tool, which could be used by investors in coutering risks in uncertain markets by simulating the different market conditions.

Discussion

Interpretation of Results

The findings of the stochastic nonlinear model indicate some important findings on the association between the capital market volatility and venture capital (VC) risk of deep tech startups. Stochastic nonlinear model exhibits a humble fit

(R^2=0.45, RMSE=1.10B) compared to linear (R^2=-0.00038, RMSE=1.245B) and benchmark model reflecting a complicated market dynamics within the deep tech VC risk. The high values of RMSE indicate a high volatility of the valuation; the negative value of R2 in linear/benchmark fit indicates poor fits. The low performance may be explained by the fact that deep tech industries are more volatile and unpredictable, and technological shocks and shifts in the market are more unstable. These results suggest that more complex approaches to nonlinear stochastic modeling may be required to determine the success or failure of startups in this field rather than relying on traditional models.

The success and failure probability as per the simulation also highlight the high risk that investors in the early stages of startup financing are exposed to especially in the high-tech sectors. The high returns that can be expected with high risks in the initial stages can also be mentioned as an indication of the expected ROI, which once again supports the necessity to promote diversification of the portfolio and risk management.

Comparison with Existing Models

The stochastic nonlinear model was a more flexible framework to model the complicated, dynamic interactions within capital markets as compared to traditional linear regression models that exhibit poor predictive power. The stochastic nonlinear model (R^2=0.45) outperforms the linear (R^2=-0.00038) and benchmark (R^2=-0.05), capturing nonlinear relationships better, though large RMSE indicates need for further refinement. Nonetheless, as indicated by the large values of RMSE, more refinement and maybe more sophisticated modeling methods (e.g. use of machine learning or advanced stochastic models) would be required to enhance the performance of the model.

Compared to state of the art, e.g. GARCH models or machine learning-driven risk models, this paper indicates that even more robust solutions cannot capture the scale of market shocks or technology-specific risks that profoundly impact startups in the deep tech space. Such models need a more subtle interpretation of industry-related dynamics, regulatory factors, and investor actions.

Limitations

There are a number of limitations that have to be admitted in this research. To start with, the data employed is restricted in both scale and scope and covers only a limited number of potential market factors and startup factors (e.g., technological readiness, quality of management team). Subsequently, the model may be performing poorly because of these missing variables, which may affect the startup valuation and VC risk. Assuming the normality in the modeling process is also a limitation. Although stochastic models such as SDEs and nonlinear GARCH are strong when used in a financial context, it can largely assume that the returns made by financial entities can be found in the normal distribution, which might not necessarily be the case with all deep tech startups. The volatility and market shocks that may be experienced in the deep tech sector necessitate alternative distributions or risk models in order to understand all the uncertainty. Lastly, although t-tests and p-values were used to evaluate the statistical significance of the model, the low R 2 and high RMSE are indicators of poor fit, implying that this method may not be able to entirely attribute the natural complexity of VC risk in deep tech investments. This weakness necessitates an additional investigation of more sophisticated, data-driven models that would allow explaining the particular problems and ambiguity of this business better.

Conclusion

This paper discusses how stochastic nonlinear models can be used to understand capital market volatility and venture capital (VC) risk of deep tech startups. The results indicate that the conventional models, which include the linear regression, do not adequately reflect the complexity and dynamics of markets on such startups which are mostly volatile and unpredictable. The nonlinear GARCH forms and stochastic differential equations (SDEs) that are used in the present analysis provide better market fluctuation and VC risk simulations, through the nonlinear interactions and uncertainty in the market. Major discoveries indicate that the start-ups at an earlier stage, especially in the high technology industry are exposed to high levels of risks in terms of investments, and the likelihood of failure is high. Nevertheless, the high returns potential highlights the issues of diversification of portfolios and strategic management of investments within the venture capitalists. Another point made by the model is the importance of market conditions, funding stage, and the type of investors to the success possibilities of startups. Practical implications to investors would be in the form of more sophisticated risk assessment tools because the traditional forecasting techniques are not sufficient to reflect the complexity of deep tech markets. Startups can make better decisions based on the risk dynamics as seen in these models by knowing how to spend the capital and position themselves in the market. Future research might involve adding grain-sized data on startup-specific attributes, including technology readiness and quality of management, and consider more advanced models, including machine learning-based models and

agent-based simulations. These developments will keep increasing the accuracy and prediction capability of VC risk measures in unstable markets.

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