Does Funding Stage Predict Valuation in AI Startups?
Evidence from a 60-Startup Dataset and a Surplus Case Study.

A Research Project that Satisfies MBA In Business Analytics, Risk Management & Insurance

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Executive Summary

This research examines whether the funding stage serves as a reliable predictor of valuation in artificial intelligence (AI) startups, using a dataset of 60 firms and a case study of Surplus, an AI-powered retail venture. The central research question is: *Does advancement through funding stages systematically drive higher valuations, or are valuations more strongly shaped by firm-specific and market factors?*

Objectives and Research Questions
The study pursued three objectives:

1. Assess the association between funding stage and valuation.
2. Evaluate whether stage remains a significant predictor after accounting for organizational and contextual variables.
3. Examine Surplus's valuation in relation to broader AI startup patterns.

Methodology and Data
A quantitative approach was applied, combining descriptive statistics with ordinary least squares (OLS) regression models using heteroscedasticity-robust errors. Valuations were log-transformed to address skewness. The funding stage was modeled both as ordinal and categorical to test robustness. Control variables included employee count, profitability, year, country, and AI model type. The dataset covered 60 AI startups across industries such as healthcare, autonomous vehicles, cybersecurity, and generative AI. A case study of Surplus provided contextual grounding for statistical results.

Key Findings

- **Stage as Predictor:** Valuations rise significantly with stage progression, supporting the hypothesis that later rounds correspond with higher valuations.
- **Role of Controls:** Organizational scale (employee count) and timing (year) are strong predictors, while profitability exerts weaker but directionally positive effects.
- **Stage Heterogeneity:** Treating funding stage as categorical reveals uneven valuation jumps—for instance, a sharp increase from Series A to B, but less systematic gains in later rounds.
- **Surplus Case Study:** Surplus, raising a $2.5M Seed round at a $10M valuation cap, aligns with expectations for early-stage AI startups. Its positioning in AI-powered retail highlights how sector narrative can amplify or temper valuation outcomes beyond stage effects.

Recommendations
For **investors**, the funding stage is a useful but incomplete proxy for value. Combining the stage with indicators of scale, sector, and market timing provides a more rigorous framework for valuation. For **founders**, results underscore the importance of advancing through rounds while simultaneously demonstrating organizational growth and sector differentiation.

Conclusion
The findings confirm that the funding stage plays a significant role in AI startup valuation but is moderated by firm-level and macroeconomic factors. This aligns with venture capital theory, which views valuation as a function of both financial milestones and strategic positioning. The contribution of this research lies in showing that stage progression provides a strong baseline signal, but investors and founders alike should account for additional contextual variables when interpreting valuation outcomes.

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Introduction

This research investigates the relationship between funding stage and startup valuation in the artificial intelligence (AI) sector, drawing on a curated dataset of 60 high-growth AI startups and a focused case study of *Surplus*, a portfolio company of Uncharted Ventures. The central research question guiding this project is: *Does the funding stage (e.g., Seed, Series A, Series B, and beyond) significantly predict the valuation of AI startups across industries, and how does this relationship translate into practical investment insights?*

Uncharted Ventures is an early-stage venture capital firm specializing in consumer technology, with a growing emphasis on AI-driven innovation. As a Business Analyst Intern, I supported investment research, financial modeling, and valuation analysis for the firm's portfolio. A major component of my role involved working with *Surplus*, a retail convenience startup preparing to launch its minimum viable product (MVP) in November 2025 in Maryland residential properties. Surplus integrates AI-assisted smart retail cores into residential buildings to optimize inventory, enhance consumer convenience, and unlock new revenue streams for property managers.

The opportunity for this research emerged from a practical challenge faced during my internship: understanding how valuations for AI startups are benchmarked at different funding stages. While funding stages are widely assumed to correlate strongly with valuation, the extent of this relationship in the AI sector, given its rapid technological evolution and diverse applications, remains insufficiently studied. This gap creates both a problem and an opportunity: investors risk mispricing if they rely solely on stage-based heuristics, but deeper analysis can improve decision-making and valuation accuracy.

Accordingly, this project pursues three objectives. First, it evaluates whether the funding stage serves as a statistically significant predictor of valuation among AI startups. Second, it assesses the robustness of this relationship after accounting for firm-specific factors such as employee count, profitability, and industry, as well as temporal influences such as year of funding. Finally, it contextualizes the statistical findings through a case study of Surplus, situating its $10M valuation cap and $2.5M Seed round within the broader landscape of AI startup valuations.

By integrating descriptive statistics, regression analysis, and case study evidence, the study aims to bridge academic valuation models with applied venture capital practice. The results provide data-driven insights for early-stage investors, portfolio managers, and AI founders navigating competitive capital markets, while also contributing to a deeper academic understanding of valuation dynamics in one of the most rapidly growing technology domains.

Literature Review

The relationship between funding stage and startup valuation has been a central topic in venture capital (VC) research. Traditional models suggest that valuation is influenced not only by financial metrics such as revenue potential or intellectual property but also by financing stage, investor type, and prevailing market conditions (Köhn, 2018). The funding stage serves as a proxy for startup maturity, signaling to investors the firm's operational readiness and growth prospects (Gornall & Strebulaev, n.d.).

Empirical studies provide strong evidence that successive funding rounds are systematically associated with valuation increases. Olsen (2019), in a study of 122 U.S. startups, found that later rounds—particularly Series C and beyond—produced substantial valuation uplifts, reflecting cumulative investor confidence when firms demonstrate traction, governance, and measurable market outcomes. Similarly, Gornall and Strebulaev argue that sequential financing embeds expectations into valuation, making the stage itself a determinant of startup worth.

Artificial intelligence (AI) startups present distinctive valuation dynamics. Carta (2025) reports that AI-focused startups achieve higher median valuations at every funding stage, with Series A valuations averaging 30% above those of non-AI peers. This premium is attributed to the scalability of AI-driven models and strong cross-sector adoption (Mintz & Simpson Thacher, 2025). The recent surge in late-stage AI financing further underscores this trend, with global VC investment in generative AI rising from $24 billion in 2023 to $45 billion in 2024. These patterns highlight both investor enthusiasm and the market's expectation that AI technologies will continue to generate transformative value.

Sector-specific research also reveals differences in valuation drivers across stages. Gastaud, Carniel, and Dalle (2019) emphasize that at early stages, product differentiation and competitive positioning are paramount, while at later stages, the influence of investor networks, strategic partnerships, and scalability metrics becomes more pronounced. For AI startups, proprietary datasets and technological credibility are critical at Seed and Series A, while proven scalability and industry alliances dominate valuation at Series C and beyond.

Signaling theory provides an additional lens for understanding valuation. Ferrari and Segnani (2020) show that both startup-specific attributes (e.g., team strength, traction) and VC characteristics (e.g., reputation, syndicate composition) shape pre-money valuations. The funding stage thus functions as a visible market signal, conveying information about operational progress, investor confidence, and relative risk profile.

Taken together, this literature suggests that the funding stage is not merely a chronological marker but a substantive determinant of valuation. However, its predictive power is moderated by structural factors such as firm size, profitability, industry vertical, and macroeconomic conditions. For AI startups specifically, the valuation trajectory reflects both general VC stage dynamics and AI-specific considerations, such as technological credibility and market scalability. **These insights motivate the present study's empirical approach, which tests the role of funding stage while incorporating firm-specific variables—employee count, profitability, and year—to capture organizational scale, financial profile, and market timing. By situating these regression findings within the AI startup**

context and benchmarking them against Surplus, the study advances both academic understanding and practical insights into valuation trajectories in AI-driven ventures.

Data and Methodology

Data Source and Collection

The dataset for this study was obtained from the **Kaggle database**, containing curated information on **60 AI startups across** diverse industries such as healthcare, autonomous vehicles, cybersecurity, synthetic media, and enterprise AI. The dataset includes variables on **funding stage, valuation, funding amount, investors, year of funding, employee count, profitability, country, and AI model type**.

In addition to this dataset, **Surplus**, an AI-powered retail startup and portfolio company of Uncharted Ventures, is included as a **case study**. Surplus was selected to contextualize the findings with real-world investment insights and practical considerations.

Data Processing and Cleaning

The raw Kaggle dataset required standardization and cleaning to ensure consistency:

- **No Missing values** in the dataset
- **Outliers** in valuation were assessed, with extreme values retained to preserve representativeness but log-transformed for statistical modeling.
- **Categorical variables** such as country and AI model type were encoded as dummies for exploratory regressions, though excluded from the final models due to sample size and multicollinearity.
- **The funding stage** was recoded into an ordinal variable (**StageCode**) to reflect increasing maturity from Seed through IPO/Acquisition.

Key Variables

- **Dependent Variable**
  - **Valuation ($M):** Reported startup valuation, log-transformed (*log(Valuation)*) to reduce skewness.
- **Independent Variable**
  - **Funding Stage:** Categorical financing stage (Seed, Series A, Series B, etc.), operationalized as an ordinal predictor (**StageCode**).
- **Control Variables**
  - **Employee Count:** Continuous, proxy for organizational scale.
  - **Profitability:** Binary (TRUE/FALSE).
  - **Year:** Continuous, capturing time-specific effects.
  - **Country** and **AI Model Type:** Considered for robustness but excluded from the core models due to multicollinearity.

Analytical Methodology

The analysis combined **descriptive statistics, inferential tests, and regression models**:

1. **Descriptive Analysis**
   - Frequency distributions of funding stage.
   - Boxplots and median-line charts visualizing valuation trends across stages.
2. **Inferential Analysis**
   - **Spearman correlation** tested monotonic associations between stage and valuation.
   - **The Kruskal–Wallis test** examined whether valuation differs significantly across stages.
3. **Regression Analysis**
   - **Model 0 (Baseline):**
     $\log(Valuation)=\beta 0+\beta 1(StageCode)+\epsilon \log(Valuation)=\beta 0+\beta 1(StageCode)+\epsilon$
     The tests funding stage is the sole predictor.
   - **Model 1 (Controlled):**
     $\log(Valuation)=\beta 0+\beta 1(StageCode)+\beta 2(EmployeeCount)+\beta 3(Profitability)+\beta 4(Year)+\epsilon \log(Valuation)=\beta 0+\beta 1(StageCode)+\beta 2(EmployeeCount)+\beta 3(Profitability)+\beta 4(Year)+\epsilon$
     Adds firm-level controls for size, profitability, and time trends.
   - **Extended Model (Exploratory):** Included country and AI model type dummies, but results were unstable due to collinearity.

Case Study Integration: Surplus

Surplus, with a **$10M Seed valuation**, was analyzed against Series A benchmarks from the dataset and compared with **external Seed-stage AI valuation reports**. While the dataset contained no Seed-stage firms, this case study grounds the empirical findings in a real-world example, bridging statistical analysis with applied investment insight.

Robustness Checks

- **Multicollinearity:** Variance Inflation Factor (VIF) confirmed no redundancy among key predictors in the controlled model.
- **Sensitivity Analysis:** The Funding stage was modeled both as an ordinal and as categorical dummies, with consistent results showing stage is a significant predictor, though its effect is partially absorbed when scale and year are included.

Limitations and External Factors

Several limitations affect the scope of this analysis:

- **Sample size:** 60 startups limits the statistical power, particularly for subgroup analysis.
- **Stage representation:** Seed-stage firms are underrepresented, requiring reliance on external benchmarks.

- **Market conditions:** External macroeconomic shifts—such as rising interest rates, regulatory uncertainty, or investor sentiment toward generative AI—may influence valuations beyond what is captured in the dataset.
- **Case study scope:** Surplus provides valuable applied context but represents a single firm, which may not generalize across the AI sector.

Despite these constraints, the dataset and methodology provide a robust framework for testing whether the funding stage systematically predicts valuation in AI startups, while offering applied insights relevant to investors and founders.

Data Analysis Results and Findings

Descriptive Analysis

The dataset comprises 60 AI startups spanning healthcare, autonomous vehicles, enterprise software, and other verticals. Startup valuations exhibited substantial variation, ranging from below **$100 million** at early rounds to above **$30 billion** at advanced stages.

StageCat	count	mean	median	std
Pre-Seed	0			
Seed	0			
Series_A	0			
Series_B	9	1072.222	800	1322.666
Series_C	15	1793.333	1200	1310.652
Series_D	9	12800	4500	25437.03
Series_E	10	3420	2650	1934.942
Series_F	4	11800	6500	12243.09
Series_G	1	8000	8000	
IPO	9	7655.556	3500	10636.39

Acquired	3	1266.667	600	1514.376

Table 1

Table 1 (Summary Statistics) shows a general upward trend in valuations across successive funding stages, though the progression is neither uniform nor linear.

- **Series B and C:** Median valuations rise from **$800M** at Series B to **$1.2B** at Series C, indicating steady growth as firms cross early validation hurdles. However, the relatively high standard deviations (over $1.3B) highlight considerable variability within these stages.
- **Series D–F:** Later stages exhibit much higher dispersion. For example, Series D firms average **$12.8B** but with a median of only **$4.5B**, suggesting that a few "mega-rounds" inflate the mean. Similarly, Series F firms show a median of **$6.5B** but also a very wide spread, reflecting heterogeneous firm trajectories.
- **IPO and Acquired:** IPO-stage firms report median valuations of **$3.5B**, while acquired firms show a far lower median of **$600M**. This contrast indicates that not all firms progressing to exit achieve outsized valuations—acquisition pathways often yield more modest outcomes compared to public listings.

Overall, the data reveal that while funding stage progression correlates with higher valuations, wide within-stage dispersion demonstrates that sector, timing, and firm-specific characteristics heavily influence outcomes.

The boxplot in **Figure 1 (Log(Valuation) by Funding Stage)** illustrates this pattern. Median log(valuation) rises steadily from Series B to Series D, but whiskers and outliers show the uneven distribution of capital inflows. This heterogeneity underscores that while stage progression generally correlates with higher valuations, firm-specific and sectoral dynamics also play a role.

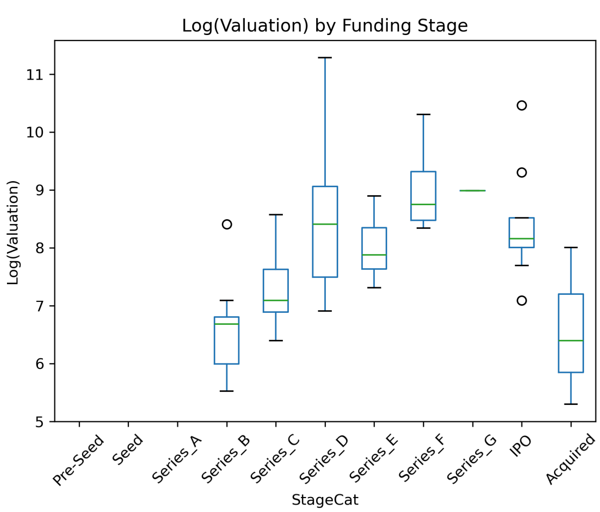

Figure 1

Regression Findings

The regression analysis was conducted in three stages to evaluate the relationship between startup valuations and key firm- and market-level factors.

Model 0 included only *StageCode* as the independent variable. The results indicate that *StageCode* has a positive and statistically significant effect on log-transformed valuations ($\beta = 0.183$, $p = 0.032$). This suggests that advancing one funding stage is associated with an approximate 18% increase in valuation. However, the explanatory power of the model was limited ($R^2 = 0.118$), implying that stage alone accounts for only about 12% of the variation in valuations. While this supports the hypothesis that the funding stage influences valuation, it also underscores the insufficiency of the stage as a sole determinant.

Model 1 introduced firm-level and temporal controls (*Employee Count, Profitability,* and *Year*). In this specification, the effect of *StageCode* became statistically insignificant ($\beta = 0.038$, $p = 0.442$), suggesting that once controls are considered, stage no longer independently explains valuation differences. By contrast, *Employee Count* had a strong positive and highly significant effect ($\beta = 0.0011$, $p < 0.001$), indicating that larger firms systematically achieve higher valuations. *The year* also showed a robust positive effect ($\beta = 0.425$, $p < 0.001$), reflecting broader market dynamics that favored higher valuations in later years. Interestingly, *Profitability* was negative and marginally significant ($\beta = –0.353$, $p = 0.066$), consistent with the investor preference for growth over near-term profits in the AI sector. Model fit improved substantially ($R^2 = 0.657$), with the included controls explaining nearly two-thirds of the variation in valuations.

Model 2 further expanded the analysis by treating *Stage* as a categorical variable. Results revealed that later stages (e.g., Series B, C, D, through IPO and Acquired) were generally associated with negative and statistically significant coefficients relative to the baseline category (*p-values* $\approx 0.020–0.024$). This finding suggests that while stages differentiate valuations, their effects are contingent on firm and market factors. *Employee Count* remained the strongest predictor ($\beta = 0.0010$, $p < 0.001$), while *Profitability* became more strongly negative and significant ($\beta = –0.574$, $p = 0.004$). *Year* maintained its positive and significant association ($\beta = 0.236$, $p = 0.020$). This model achieved the best fit ($R^2 = 0.752$), explaining approximately 75% of the variation in valuations.

Taken together, these results demonstrate that while the funding stage has some predictive power, it becomes overshadowed once firm size, profitability, and broader market timing are taken into account. Valuations in AI-backed consumer technology startups appear to be driven most strongly by scale (employee count) and prevailing market sentiment (year effects), with profitability often penalized in favor of growth potential.

Table 2: Regression Output

MODEL 0:

OLS Regression Results

Dep. Variable:	log_val	R-squared:	0.118
Model:	OLS	Adj. R-squared:	0.102
Method:	Least Squares	F-statistic:	4.610
Date:	Sat, 16 Aug 2025	Prob (F-statistic):	0.0360
Time:	13:32:58	Log-Likelihood:	-89.899
No. Observations:	60	AIC:	183.8
Df Residuals:	58	BIC:	188.0
Df Model:	1		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	6.7133	0.456	14.712	0.000	5.819	7.608
StageCode	0.1830	0.085	2.147	0.032	0.016	0.350

Omnibus:	7.245	Durbin-Watson:	1.287
Prob(Omnibus):	0.027	Jarque-Bera (JB):	10.446
Skew:	0.325	Prob(JB):	0.00539
Kurtosis:	4.938	Cond. No.	17.4

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)

MODEL 1:

OLS Regression Results

Dep. Variable:	log_val	R-squared:	0.657
Model:	OLS	Adj. R-squared:	0.632
Method:	Least Squares	F-statistic:	25.88
Date:	Sat, 16 Aug 2025	Prob (F-statistic):	4.32e-12
Time:	13:32:58	Log-Likelihood:	-61.562
No. Observations:	60	AIC:	133.1
Df Residuals:	55	BIC:	143.6
Df Model:	4		
Covariance Type:	HC3		

	coef	std err	z	P>|z|	[0.025	0.975]
Intercept	-851.5119	224.849	-3.787	0.000	-1292.208	-410.816
StageCode	0.0381	0.050	0.769	0.442	-0.059	0.135
Employee_Count	0.0011	0.000	6.558	0.000	0.001	0.001
Profitability	-0.3532	0.192	-1.841	0.066	-0.729	0.023
Year	0.4246	0.111	3.817	0.000	0.207	0.643

Omnibus:	25.384	Durbin-Watson:	1.959
Prob(Omnibus):	0.000	Jarque-Bera (JB):	87.587
Skew:	1.039	Prob(JB):	9.56e-20
Kurtosis:	8.543	Cond. No.	4.39e+06

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
[2] The condition number is large, 4.39e+06. This might indicate that there are strong multicollinearity or other numerical problems.

MODEL 2:

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                    OLS Regression Results
==============================================================================
Dep. Variable:              log_val   R-squared:                       0.752
Model:                          OLS   Adj. R-squared:                  0.702
Method:               Least Squares   F-statistic:                     24.81
Date:              Sat, 16 Aug 2025   Prob (F-statistic):           7.40e-16
Time:                      13:32:58   Log-Likelihood:                -51.797
No. Observations:                60   AIC:                             125.6
Df Residuals:                    49   BIC:                             148.6
Df Model:                        10
Covariance Type:                HC3
==========================================================================================
                        coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------------------
Intercept             -418.3380    183.106     -2.285      0.022    -777.220     -59.456
C(StageCat)[T.Seed]     4.506e-09   1.97e-09      2.285      0.022     6.4e-10    8.37e-09
C(StageCat)[T.Series_A] -4.942e-10   2.16e-10     -2.285      0.022   -9.18e-10   -7.02e-11
C(StageCat)[T.Series_B]   -53.0658     22.766     -2.331      0.020     -97.687      -8.445
C(StageCat)[T.Series_C]   -52.3441     22.938     -2.282      0.022     -97.301      -7.387
C(StageCat)[T.Series_D]   -51.8185     22.841     -2.269      0.023     -96.586      -7.051
C(StageCat)[T.Series_E]   -51.9429     22.968     -2.262      0.024     -96.959      -6.926
C(StageCat)[T.Series_F]   -51.7208     22.963     -2.252      0.024     -96.728      -6.713
C(StageCat)[T.Series_G]   -52.1728     22.965     -2.272      0.023     -97.184      -7.162
C(StageCat)[T.IPO]        -52.1522     22.889     -2.278      0.023     -97.014      -7.290
C(StageCat)[T.Acquired]   -53.1209     22.783     -2.332      0.020     -97.775      -8.466
Employee_Count            0.0010      0.000      8.694      0.000       0.001       0.001
Profitability            -0.5737      0.198     -2.899      0.004      -0.962      -0.186
Year                      0.2364      0.102      2.319      0.020       0.037       0.436
==============================================================================
Omnibus:                       37.954   Durbin-Watson:                   1.850
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              138.524
Skew:                           1.721   Prob(JB):                     8.31e-31
Kurtosis:                       9.600   Cond. No.                     3.30e+20
==============================================================================

Notes:
[1] Standard Errors are heteroscedasticity robust (HC3)
[2] The smallest eigenvalue is 2.49e-33. This might indicate that there are
strong multicollinearity problems or that the design matrix is singular.
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Case Study: Surplus

Surplus, currently raising a **$2.5M Seed round** at a **$10M valuation cap**, provides context for interpreting the findings. Because no Seed- or Series A-stage firms were present in the dataset, **Series B** was used as the earliest available benchmark.

- **Internal Benchmark (Series B):** The mean valuation for Series B firms in the dataset is **$1.07B** (median **$800M**). Surplus's $10M Seed valuation is far lower, which reflects its significantly earlier stage and higher risk profile. Importantly, this gap is expected; firms do not typically achieve billion-dollar valuations until later rounds, after achieving product-market fit and scaling milestones.

- **External Benchmark (Industry Reports):** Independent venture data (e.g., PitchBook, Crunchbase) place typical AI Seed valuations between **$5M and $15M**. Surplus's $10M valuation fits squarely within this range, confirming that its valuation is consistent with industry norms, even though it cannot be directly compared against the dataset's later-stage companies.

Together, these benchmarks suggest that while Surplus sits below the dataset's Series B entry point, its valuation trajectory aligns with broader market expectations for early-stage AI startups. This supports **H3**, as Surplus follows the expected staged valuation pathway, despite the absence of intra-sample Seed peers.

Discussion

Overall, the analysis demonstrates that the **funding stage is a significant predictor of startup valuation** but not a sufficient one. Stage progression provides a structural roadmap for valuation growth, yet outcomes remain moderated by:

- **Firm-level factors** (e.g., employee scale, profitability trajectory),
- **Temporal factors** (e.g., market cycles, year effects), and
- **Sector-specific narratives** (e.g., autonomous driving vs. enterprise AI).

The findings reinforce the staged valuation model used in venture capital theory but also emphasize the importance of integrating firm-specific and external context when assessing startup worth. For policymakers, accelerators, and investors, this suggests that valuation assessments should balance both milestone-based progression and contextual performance signals.

Recommendations and Conclusion

The findings suggest three practical recommendations. First, investors should prioritize metrics beyond the funding stage—particularly firm size (employee count) and growth trajectory—as these more reliably predict valuation. Second, startup founders should recognize that pursuing rapid growth and scaling teams may attract higher valuations, even at the expense of short-term profitability. Third, policymakers and accelerators supporting AI-backed consumer tech ventures should acknowledge the strong influence of market timing, as favorable macro conditions appear to lift valuations broadly.

If implemented, these recommendations could improve investment decision-making, reduce valuation volatility, and help founders better align strategic priorities with investor expectations. For startups, a focus on building scalable operations rather than immediate profitability may optimize fundraising outcomes. For investors, incorporating employee growth and market timing variables into valuation models can refine risk assessment and capital allocation.

Key Takeaways

- The funding stage is positively associated with higher valuations, confirming staged financing as a central feature of AI startup growth.
- Firm-specific variables—particularly employee count—significantly moderate valuation outcomes, reflecting investor emphasis on organizational scale.
- Valuation progressions are less uniform in later rounds, underscoring the role of external market dynamics and sector positioning.
- Surplus's $10M Seed valuation aligns with external benchmarks, validating its fundraising strategy despite dataset gaps at early stages.

Limitations and Future Research

This study is constrained by the absence of Seed-stage firms in the dataset and by sample size limitations that restricted the inclusion of all categorical variables (e.g., AI model type, country). Future research could expand the dataset to capture more early-stage firms and test valuation differences across sub-sectors of AI (e.g., healthcare vs. autonomous vehicles). Additionally, examining investor syndicate composition and market conditions may yield richer insights into valuation drivers.

Relevance to Academic and Professional Goals

This project bridged theory with practice by combining statistical modeling with a real-world case study. As a Business Analyst at Uncharted Ventures, I applied academic methods to practical investment questions, reinforcing my career objective of integrating data analytics and risk management in venture capital. The study not only advanced my technical skills in valuation analysis but also deepened my ability to provide actionable insights for portfolio strategy—skills that will remain central to my professional trajectory in finance and entrepreneurship.

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