

Time is money? The role of cadence and serial entrepreneurship in venture capital funding outcomes of startups

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Abstract

Although venture capital is widely recognized as a driver of startup growth, existing research often overlooks temporal aspects, particularly the time between funding rounds. This study introduces the concept of fundraising “cadence” and examines its influence, along with founder experience and startup maturity, on critical funding outcomes. The analysis investigates how fundraising cadence impacts both funding growth and the likelihood of exceeding industry benchmarks, and how these dynamics vary by founder type. Utilizing a dataset of 266 U.S.-based technology startups that have completed Series A until D funding rounds, this research reveals three key findings. First, startups with relatively longer intervals between funding rounds tend to achieve greater funding growth, particularly in early stages. Second, although serial entrepreneurs raise venture capital faster, this speed does not necessarily lead to better funding outcomes overall, suggesting that fast fundraising may be a favorable signal without ensuring better funding outcomes. Third, startup maturity slows fundraising cadence and reduces the likelihood of exceeding stage-specific industry benchmarks. These findings position fundraising cadence as a strategic lever, rather than a passive by-product of growth. By extending signaling and staged financing theory into the temporal domain of funding behavior, this study contributes on how timing decisions can shape venture financing trajectories.

Keywords: Venture Capital, Entrepreneurial Finance, Serial Entrepreneurship, Startup Financing, Survival Analysis.

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1. Introduction

Startups are widely recognized as drivers of innovation, job creation, and economic growth (Cole et al., 2015; Khaustov, 2023). Venture Capital (VC) firms play an essential role in this process by providing much-needed financial resources to firms. Yet, less than 1% of startups are backed by Venture Capital (Oranburg, 2016), and those that are make up less than 1% of all privately held firms. However, measured as of December 2019, these startups account for about 50% of total revenue and represent more than 75% of the market capitalization of publicly traded companies in the U.S. (Lerner & Nanda, 2020). They also account for almost half of all initial public offerings (IPOs) in the U.S. (Janeway et al., 2021).

Startups that secure VC backing have been shown to outperform peers in terms of R&D intensity, IPO likelihood, and market capitalization (Lerner & Nanda, 2020; Zhong, 2023). They are shown to disproportionately contribute to innovation, accounting for 62% of the R&D spending of all public companies in the U.S. (Gornall & Strebulaev, 2015). Employment is another area of impact, with a 10% increase in VC linked to a 2.6% increase in new firms, a 2.9% rise in employment, and a 3.9% increase in total payroll among small firms (Cole et al., 2015). These numbers underline the disproportionate influence of the small number of VC-backed firms on our economies, and taken together, these substantial contributions demonstrate the pivotal role of VC in driving innovation and broader economic growth. Beyond performance metrics, however, the internal dynamics of how startups raise capital, especially the timing and pacing, may explain their competitive edge.

In the VC context, fundraising refers to the sequential process through which startups raise external equity capital from institutional investors to finance their market expansion, product development, and operational scaling. Each round is typically linked to specific

performance or development milestones (Gompers & Lerner, 2001; Gorman & Sahlman, 1989), which reflect the startup’s progress along its lifecycle. Although a few startups proceed beyond Series D fundraising rounds, the majority of VC activity occurs between the Series A to D stages, which are often classified as the “growth stage” (Davila et al., 2003; Kerr et al., 2014).

It is within this framework that fundraising cadence – the timing between successive fundraising rounds – becomes a potential driver of competitive advantage and strategic momentum. While most existing research relies on broader annual measurements of timing between rounds (Hsu, 2004), this study adopts a more granular, month-based approach. We base our empirical analysis on panel data from 266 U.S. startups that have raised VC from Series A up through Series D. The analysis applies a combination of OLS regressions and survival analysis to examine how cadence between funding rounds, founder experience, and industry factors affect fundraising outcomes. In addition, the study explores the moderating effect of serial entrepreneurship on the relationship between fundraising cadence and funding outcomes. The overarching research question of this paper is as follows:

How does funding cadence and serial entrepreneurship impact the venture capital funding outcomes of startups?

We contribute to a more complete understanding of startup fundraising behavior by analyzing the internal timing dynamics within the VC fundraising process, including the influence of serial entrepreneurship and industry context. From a managerial and entrepreneurial standpoint, the findings of this paper offer practical implications for both founders and investors. Founders may use these insights to better plan their fundraising efforts and strategies. In addition, they can better understand the implications of timing and serial entrepreneurship within funding rounds on success, growth, and investor perception. At the same time, VC investors and

other investors investing in the growth stages of startups may benefit from deeper insights into what shapes funding trajectories, namely fundraising cadence, serial entrepreneurship and industry context, allowing them to identify promising signals and enable them to tailor their initial investments as well as follow-on investments more effectively.

2. Literature

How startups are financed is one of the most fundamental questions in enterprise research (Cassar, 2004). Analyzing the specific fundraising dynamics related to VC funding is essential to understand the drivers of startup growth and success. Venture capital (VC) can be defined as a source of financing whereby a financial investor takes an equity stake in a private company that, in general, is starting up or will grow fast in the following years (Berlin, 1998; Gorman & Sahlman, 1989).

VC funds are often considered the only viable source of financing to start a company, particularly for startups built around intangible assets, with limited collateral or early revenue streams (La Rocca et al., 2011). Most of these firms are typically small, young, and face high levels of uncertainty and information asymmetry. VC investors are the organizations that step in to finance these high-risk, high-reward projects by purchasing equity stakes while the firms are still privately owned and controlled (Gompers & Lerner, 2001). By doing so, they play a pivotal role in providing funding to startups and small businesses, which often lack the resources, capabilities, and expertise that would be necessary to secure traditional forms of financing (Zhong, 2023).

While funding is a major driver of startup success, not all VC-backed ventures perform equally well, receive the same funding amounts, nor do they share the same likelihood of

success. Emerging evidence indicates that there are several aspects that might influence how startups grow, maintain their momentum, and signal performance.

One of these signals may be fundraising cadence, as there may be a link between fundraising cadence and how this signal is perceived by investors and other market participants. Ewens & Townsend (2018) find that successfully completed financing rounds act as a positive signal to potential future investors, other stakeholders, and even potential customers. In addition to attracting capital, fundraising cadence may also influence the scale of funding received or the likelihood of exceeding industry benchmark funding amounts, yet little is known about these outcome effects.

A second key determinant of funding outcomes is founder experience, in particular serial entrepreneurship and what it signals to investors. Signaling theory and founder signals are well-researched within the VC ecosystem and historically have received strong attention. Hsu (2007) discusses anecdotal evidence suggesting that serial entrepreneurs may be able to raise early growth-stage funding faster and at higher valuations with each successive startup that they found, while Zhang (2011) provides empirical evidence that serial entrepreneurs raise subsequent funding rounds faster than novice founders. The impact of founder experience on cadence of funding rounds, particularly its impact on funding outcomes, however, remains largely underexplored. Overall, research finds that many founder characteristics are often interpreted by VC investors as strong and positive signals of startup potential and quality (Nahata, 2019; Rijssen et al., 2024; Zhang, 2011). While these findings highlight a clear timing advantage for serial entrepreneurs, little research has examined how fundraising cadence ultimately impacts funding quality and subsequent venture performance.

A third aspect that may significantly influence a startup's funding outcomes could be the industry in which the firm operates. Business models and strategic priorities of young ventures are shaped by industry context (Zott & Amit, 2008), and this context is often of higher relevance to startups than compared to already established firms. Cassar (2004) finds that the reason could be the far more pronounced financing constraints these young firms in capital-intensive or high-risk industries face. Moreover, industry context affects not only operational factors but also growth and survival rates. These differences are especially pronounced in the technology sector, which has emerged as the dominant industry for startup activity in recent years and is said to have increased by roughly 47% within the last decade (Wu & Atkinson, 2017). By focusing on the tech-driven industries and further analyzing cadence in conjunction with serial entrepreneurship and industry context, this paper addresses the underexplored role of fundraising cadence. In doing so we contribute to a better understanding of how cadence, serial entrepreneurship, and industry context shape startup funding outcomes.

3. Data and sample characteristics

3.1 Data sources and sample criteria

Our data were sourced from Tracxn. This platform focuses on the private investment market and provides a wide coverage of startup related data, including a detailed overview of startup funding rounds. In order to build our sample, we first selected all US based firms that raised growth-stage funding rounds from Series A through Series D, ensuring complete data on fundraising cadence across all funding rounds. The most recent Series D round in our sample was completed in January 2025, and the earliest Series D round was completed in 2010. For startups lacking complete information in Tracxn, particularly the information related to funding

rounds prior to series D, the missing information was obtained via the platform Gain.pro.

Gain.pro is a private market intelligence platform from the Netherlands, comparable to Tracxn, which focuses on deal-sourcing automation.

In cases of a single funding round being spread across multiple tranches under the same round label (e.g., Series C), but recorded with different closing dates and partial amounts, the aggregated total of these tranches was used. The date of the final tranche was taken as the round's closing date, provided that all entries were marked as the same round. If Gain.pro failed to provide the data missing from Tracxn, the information was retrieved using Crunchbase. If necessary, an ultimate verification was conducted via the official website of the startup. The final dataset retained only those firms that had truly completed and verified funding round data for all four stages (Series A through D).

We focus on startups active in the technology sector, and use the tech industry sub-classifications as provided by Tracxn. This focus reflects the dominance of the technology industry in recent startup activity and enables a structured comparison between the startups in our sample. Furthermore, limiting the scope to a single broad industry reduces variability from unrelated sector-specific capital needs or funding dynamics.

We subsequently filtered the data to retain the startups that had received their funding exclusively from VC firms, excluding angel investors or other non-VC sources. Finally, startups were further filtered by founder background, comprising initially 197 serial entrepreneurs, and 97 first-time founders. Duplicate entries were removed, and the founders' background was manually double-checked via Tracxn, Crunchbase, and LinkedIn profiles to ensure accurate classification. This left a total of 266 startups in the dataset, of which 168 founded by serial entrepreneurs, and 98 by first time founders.

Given the structure of our dataset and the timeframe spanning from 1999 (the founding date of the oldest startup that managed to secure a Series D funding round) until 2025 (the most recent Series D funding round), several control variables were included to account for confounding effects. The selected period (i) spans across both economic growth and contractionary phases, thus mitigating endogeneity created by macroeconomic factors (Ivashina & Scharfstein, 2010), and (ii) allows sufficient time to track fundraising cadence and funding outcomes.

One possible element of concern is the non-randomness of our sample. Indeed, firms who manage to secure several subsequent rounds of VC funding are generally the most successful ones. This raises the question whether the relationship between funding cadence, serial entrepreneurship and funding growth may be driven by the startup's performance. We believe to alleviate this concern specifically because we examine *only* successful startups in our sample, therewith limiting the concern that the relation between our different variables of interest is driven by firm performance, as it is shared by all firms. In other words, although the non-randomness concern cannot be alleviated completely, we believe that this is not particularly problematic in our study, and that a comparison amongst successful startups gives the cleanest analysis when it comes to investigating the relationship between fundraising cadence and the other variables of interest in our study.

3.2 Variables

Dependent variables

The dependent variable *fundraising cadence* measures the number of months elapsed between two consecutive funding rounds and is calculated for three transitions per startup: Series $A \rightarrow B$, $B \rightarrow C$, and $C \rightarrow D$.

This variable captures potential informational, strategic and signaling relevance of *when* capital is raised, not just *how much* (Jeong et al., 2020; Qi, 2022). While prior research has used broader annual measures (Hsu, 2004), this study adopts a month-based approach to better reflect the pace of activity within the VC industry, particularly in high-growth tech sectors, where financing decisions may depend on short-term milestone achievement. Measuring in months, therefore, allows the detection of subtle but potentially meaningful differences that would remain undetected in yearly aggregates or other non-granular measures.

The second dependent variable used in our analysis is *funding growth*, which captures the change in capital raised between two successive funding rounds. It is expressed as a percentage increase or decrease and follows a simple calculation:

$$\text{Funding Growth Rate (\%)} = \left(\frac{\text{Funding Amount}_{t+1} - \text{Funding Amount}_t}{\text{Funding Amount}_t} \right)$$

Where:

funding amount_t stands for the amount raised in the earlier round (e.g., Series A)

funding amount_{t+1} stands for the amount raised in the subsequent round (e.g., Series B)

This formulation aligns with conventional approaches for measuring relative performance or change (Duff & Lippman, 2021) and allows for meaningful comparison across firms, regardless of their absolute funding size. It is well-suited for VC contexts due to its substantial variation in round sizes.¹

¹ All growth values were converted into decimals (e.g., 150% = 1.50), ensuring consistency and ease of interpretation of the regression results. Negative growth values and cases of extreme growth were explicitly retained in the main models as they may carry important insights into startup fundraising dynamics.

The final dependent variable of interest is *benchmark exceeding funding (BEF)*. This binary variable assesses fundraising success, and is constructed by comparing each startup's funding amount for a given round to the median amount raised within its industry sub-sector and stage. If the startup raised more than the sub-sector median, the dummy was coded 1; otherwise, it was coded as 0. Median values were based on Tracxn industry-level data benchmarks and the related by funding stage. In the venture capital literature, success is often defined more broadly. Common definitions include a successful exit via IPO or acquisition (Gompers & Lerner, 2001; Nahata, 2008), achieving high market capitalization (Jeng & Wells, 2000), or raising multiple subsequent rounds of VC (Lahr & Trombley, 2020). However, given that all firms in the dataset completed each round, defining success as round completion would be analytically redundant. Other methods also fail to capture the potential granular variation. We propose an alternative approach: defining success as those startups that showcased funding that exceeded the sub-sector's median round size. This benchmark indicates that the startup raised more than 50% of its sector peers, thus outperforming its peers for that specific funding round (e.g., Series A).

Explanatory variables

Consistent with prior literature, this study captures *serial entrepreneurship* as a binary variable indicating whether the startup was founded by a repeat founder, coded as 1, or a first-time founder, coded as 0. This classification is in line with several empirical studies that distinguish founders based on their prior entrepreneurial experience (Nahata, 2008; Parker, 2012). Serial entrepreneurs are typically defined as founders who previously founded one or more ventures, regardless of the venture's success, and who leverage networks, accumulated knowledge and credibility in subsequent ventures (Gruber et al., 2008; Hsu, 2007). The binary

format is chosen for clarity and because the majority of existing research treats entrepreneurial background as a constant signal rather than a continuous scale.

The *industry* variable is recorded as a categorical variable representing the firm's tech sub-sector, using the predefined classification system provided by Tracxn. The main categories include: *FinTech*, *High Tech*, *EdTech*, *Enterprise Applications*, *HealthTech*, and a residual category labeled *Others*. Several sub-sectors from the main dataset whom did not meet the minimum sample size for separate statistical analysis, were aggregated under *Others*. The *industry* variable allows to capture any variations in funding dynamics that may be driven by the type of tech occupation that the startup is involved with.

Importantly, these classifications within the *industry* variable were also used in the construction of the *BEF* variable, where sub-sector funding medians were taken directly from Tracxn for each stage (Series A-D) to account for inherent variation in funding amounts. For the *Others* category, the benchmark was calculated as the aggregated average of the individual medians of the included sub-sectors.

The *funding stage* variable is recorded as a categorical variable identifying the specific round transition between subsequent funding rounds for each startup. It differentiates between the three growth-stage transitions examined in this study: Series A→B, Series B→C, and Series C→D. Each observation in the long-format dataset represents one of these stage transitions, which enables round-level analysis of cadence, growth, and success dynamics. This variable is included to control for structural differences in funding behavior across stages, as early growth-stage and later-stage rounds often differ in terms of funding amounts and investor types (Davila et al., 2003; Gompers & Lerner, 2001). Additionally, a successfully closed prior funding round

may send a strong signal to prospective investors, affecting both access to capital and the pace of future funding (Ewens & Townsend, 2018).

Control variables

Startup age is measured as the number of years between a firm’s founding date and the year 2025. Startup age influences growth and funding outcomes (Colombo & Grilli, 2005; Hsu, 2007). Including this measures as a control variable aligns with prior literature (Lahr & Trombley, 2020; Nahata, 2008) and allows us to disentangle the effects of fundraising cadence and serial entrepreneurship from broader lifecycle effects.

The binary variable *single lead investor* is coded as 1 if the round was led by a single investor and 0 if led by multiple investors. It is common in VC research to control for investor characteristics, particularly the composition of investor syndicates (Gompers & Lerner, 2001; Manigart et al., 2022). While some studies suggest the type of investor may not notably influence startup performance directly, the presence of a single lead investor versus a syndicate may affect other variables. Table A.1 in the appendix provides an overview and summary of the variables used in our analyses.

3.3 Sample properties and descriptives statistics

Table 1 presents the descriptive statistics of the sample, comprising 798 funding round transitions from 266 U.S.-based, VC-backed startups. The average time between successive funding rounds is approximately 20 months, with variation ($SD = 13.22$), while the median (17 months) is slightly lower. Some cases stand out with ranges from immediate follow-on rounds (0 months) to gaps of up to 122 months. On average, funding amounts per round equal roughly

\$40.5M, the median is lower at \$21M, highlighting the overall skewed nature of VC funding dynamics.

Startups raise, on average, nearly twice as much capital in subsequent funding rounds during the growth stage (mean growth = 1.94), with substantial variation (SD = 5.71) across firms. This variation can be tied back to a small number of firms that experience extreme cases of growth (up to 143 times), while other startups raise less or even experience negative funding growth (min = -0.75). Roughly 77% of startups raise funding amounts that exceed their respective industry-stage median.

Approximately 63% (n = 168) of the founders within the sample are serial entrepreneurs, revealing a strong presence of repeat founders in VC-backed firms. Startups in the sample have an average age of 12.4 years, and only 8.6% of rounds were led by a single investor, indicating that investor syndicates dominate the funding process during a startup's growth stage.

Insert Table 1 about here

Table 2 displays the descriptive statistics by funding transition. Several patterns emerge: funding amounts and inter-round cadence increase steadily across stages, while funding growth rates decline. This pattern likely reflects a moderate growth pace driven by larger base funding sizes in later stages. BEF rates remain relatively stable, with only a small drop during the B to C transition. Maximum values, particularly for funding growth and amounts, are substantially higher in the earlier stages. This indicates greater volatility and upside potential in earlier stages. A one-way ANOVA (see Table A.2 in the appendix) confirms that these differences across funding stages are statistically significant for funding amount, cadence, and growth.

Insert Table 2 about here

Table 3 presents the differences between serial entrepreneurs and first-time founders. Serial entrepreneurs raise follow-on funding rounds in a shorter timeframe (mean = 19.1 months; median = 16 months) compared to first-time founders (mean = 21.5 months; median = 19 months). This indicates that serial entrepreneurs require less time to raise subsequent funding rounds at the growth stage, whereas first-time founders exhibit, on average, a slightly higher likelihood of exceeding the industry-stage funding benchmark (BEF = 83%). A similar pattern is observed for funding growth, where repeat founders raise, on average, 202% more capital in subsequent funding rounds, while first-time founders achieve a lower average growth of 181%.

Insert Table 3 about here

4. Empirical analysis

4.1 Fundraising cadence

We use a Cox (1972) proportional hazard model to estimate the relation between fundraising cadence and serial entrepreneurship. This is a semiparametric regression model that makes no assumptions about the shape of the baseline hazard function, while allowing us to condition the time until the next round of financing on a number of control variables (Cox, 1972). We take the hazard to be the next round of financing; the hazard rate for the j th startup can then be specified as follows:

$$h_j(t) = h_0(t) \exp (\beta_1 \text{ serial entrepreneurship}_j + \beta_2 \text{ industry}_j + \beta_3 \text{ funding stage}_j + \beta_4 X_j) \quad (1)$$

Where:

t = the time (in months) between subsequent funding rounds

j = startup

The coefficient β_i is our coefficient of interest and estimates to what extent the hazard rate of serial entrepreneurs exceeds the rate of first time entrepreneurs. Industry, funding stage, and several control variables (startup age and single lead investor) are included as covariates in the model. Given all startups within the sample have raised rounds from Series A to D, the data is fully observed for every event and is therefore free of right-censoring (Allison, 1984).

Table 3 shows the results of the Cox regressions. Hazard ratios are reported as $\exp(\beta)$, where values above 1 indicate an increase in the hazard, i.e. obtaining the next round of funding faster, for each unit change in the predictor variable. Columns 1 and 2 present the effects across all funding stages, using the series A to B transition as the reference group. Columns 3 through 5 present the stages separately.

Insert Table 4 about here

Our results show that startups founded by serial entrepreneurs raise follow-on financing rounds significantly faster compared to startups founded by first-time entrepreneurs. The hazard ratio for the serial entrepreneurship variable indicates a significant increase of 35.6%, implying that startups founded by serial entrepreneurs progress through funding rounds approximately 36% faster than their first-time counterparts. This result aligns with Zhang (2011), who also documents a significant speed advantage for serial entrepreneurs in early-stage financing rounds.

Furthermore, startup age is negatively associated with fundraising cadence. Each additional year in a startup's age is associated with an 8.3% decrease in the hazard rate, meaning that older startups take longer to secure subsequent funding. This is in line with prior literature that closely follows the view of a startup's lifecycle in which younger firms often generate stronger investor interest, driven by novelty, potential, or hype (add reference). Early-stage investors frequently tolerate uncertainty in this instance in exchange for a much higher upside potential. As startups mature, however, later-stage investors shift away from a narrative-driven focus to proven business models and financial metrics such as revenues or profit margins, rather than initial growth or novelty, therewith potentially slowing follow-on capital raises.

Finally, the results in column 1 indicate that startups who raise funding in the B to C, or in the C to D transition, have a 21.7%, and 22.5% respectively, lower hazard completion compared to those in the A to B transition. This stage-based pattern is further supported by the stage-specific robustness checks (columns 3-5), which reveal that the significant advantage of serial entrepreneurs in fundraising cadence is supported through funding stage transitions. Additionally, there is modest evidence that startups founded by serial entrepreneurs raising capital in early stages (A to B) have a 26.1% increased likelihood of securing the next funding round ($\beta = 1.261$), holding all else constant. Serial entrepreneur founded startups within later stages, particularly B to C even demonstrate a 56.5% increased likelihood to raise follow-on funding compared to first-time entrepreneurs ($\beta = 1.565$).

These signals may help firms navigate larger and more complex financing rounds, whereas at later stages (C to D), the positive effect of serial entrepreneurship on fundraising cadence still remains, yet only moderately. The hazard ratio indicates a 28.1% increase in the likelihood of obtaining the next funding round at any point in time. At this point, investors are

prioritizing firm-level performance indicators like market share or revenue growth per customer over the founders' background, thus reducing the marginal effect of entrepreneurial experience. This also matches economic theories that emphasize information asymmetry in early growth, which then gradually resolves as firms mature.

Notably, when turning to the interaction effect (column 2), between serial entrepreneurship and startup age, we find this term to be significantly positively associated with fundraising cadence. This suggests that younger startups founded by serial entrepreneurs can raise follow-on funding more quickly than more mature startups, as seen from their 10.9% increased likelihood to secure follow-on funding, holding all other variables constant ($\beta = 1.109$). These results underscore the non-monotonic nature of the cadence advantage of serial entrepreneurs depending on firm age.

Figure 1 displays Kaplan-Meier curve, or survival-function by founder type. The figure shows how fast startups founded by serial entrepreneurs obtain the required funding series (the funding cadence) compared to startups founded by first time founders. The shaded areas around each curve represent the 95% confidence intervals for the survival probability estimates. As shown in Figure 1, startups that are founded by serial entrepreneurs can reach their subsequent funding rounds within the growth stage more quickly than those founded by first-time founders. The survival curve for serial founders (blue) declines at a faster rate, indicating shorter durations between funding rounds. This difference is statistically significant according to the log-rank test ($p = 0.013$). Furthermore, the number of startups “at risk” of raising their next round declines steadily over time, with 291 first-time and 507 serial-founder startups at 0, dropping to just 6 and 12, respectively, by month 60. As the curve flattens significantly after the 60-month mark, the x-

axis was capped for readability purposes. Interestingly, only serial entrepreneurs remain visible past approximately 74 months, though only at very small numbers.

Insert Figure 1 about here

4.2 Funding growth

In order to test whether fundraising cadence affects funding growth rate between rounds, we use a OLS regression model. The dependent variable captures the relative increase in funding amount from one round to its subsequent round as a growth ratio (e.g., 2.5 = 150% growth). The main independent variable of interest is funding cadence, measured in months. The model includes controls for serial entrepreneurship, startup age, lead investor structure, as well as industry and stage fixed effects. FinTech is set as the reference category for industry. The model is as follows:

$$\text{Funding growth}_{j,t} = \beta_0 + \beta_1 \text{fundraising cadence}_{j,t} + \beta_2 \text{serial entrepreneurship}_{j,t} + \beta_3 \text{startup age}_{j,t} + \beta_4 \text{single lead investor}_{j,t} + \beta_5 \text{industry}_{j,t} + \beta_6 \text{funding stage}_{j,t} + \epsilon_{j,t} \quad (2)$$

Table 5 presents the results of the OLS regression. In column (1), we can see that there is a statistically significant positive relationship between fundraising cadence and funding growth. In particular, each additional month elapsed between funding rounds is associated with a 5.6% increase in follow-on funding. Economically, this means that a slight delay in the next funding round may allow startups to gain further traction, reach more favorable milestones, or negotiate from a stronger position, all possibly leading to larger funding growth. However, this effect has

practical limits as delaying too long once the fundraising process has begun may signal weak traction or investor hesitation. Startups must therefore balance timing gains, with maintaining positive market signals, we turn to this point later. Surprisingly, serial entrepreneurs do not seem to be able to secure an increased funding growth.

Insert Table 5 about here

The presence of a single lead investor has a strong positive and statistically significant effect ($\beta = 2.443$). Later-stage transitions, B to C ($\beta = -1.308$) and C to D ($\beta = -1.568$), are associated with a significantly lower funding growth compared to the transition from Series A to B. This highlights that as startups mature, incremental funding growth becomes more limited, potentially due to stricter due diligence, rising valuation caps, or increased competition and the need for proven business models and strong financial metrics. Another potential explanation may lie in the pecking order theory, which suggests that as startups mature and develop track records, they start to prefer internal financing or debt over equity financing to avoid dilution. This may reduce reliance on large equity rounds and thereby reduce observed funding growth at later stages.

Column (2) includes interaction terms paper between fundraising cadence and serial entrepreneurship ($\beta = 0.051$) and the interaction between serial entrepreneurship and startup age. Only the former is marginally statistically significant, with the magnitude of the coefficient very much in line with the results presented in column 1. This suggests that while fundraising cadence matters, its benefits are not meaningfully impacted by prior founder experience or firm maturity in this model specification.

Column (3) tests the original model using an outlier-trimmed dataset, which excludes extreme growth values above the 99th percentile. The results support the robustness of the key findings. Fundraising cadence remains significant and positive ($\beta = 0.023$, $p < 0.01$), with slightly lower magnitude. This result indicates that the positive relationship between fundraising cadence and funding growth is not driven by extreme outliers. Moreover, all other variables additionally show no meaningful deviation from the original model.

Column (4) further confirms this robustness by using the same outlier-trimmed dataset, but this time includes the interaction terms. While the fundraising cadence coefficient ($\beta = 0.017$, $p < 0.01$) remains significant, the interactions remain insignificant, underlining once more that founder type and firm maturity do not significantly alter the dynamic between cadence and growth. The potential economic signal here is that when noise is reduced through outlier trimming, fundraising cadence consistently demonstrates a positive impact on capital magnitude, further indicating that timing decisions may be an underleveraged tool in fundraising strategies.

Taken together, these regression models show that fundraising cadence plays a significant role in influencing relative funding growth, especially in early as well as mid- growth stage rounds. However, serial entrepreneurship and startup age are not directly linked to any influence on the magnitude of follow-on funding. In addition, interaction terms slightly distort these effects in some models and do not lead to a more predictive model.

4.3 Logit regression

Building on the findings of the previous section, a logistic regression model is employed to estimate the impact of fundraising cadence and serial entrepreneurship on benchmark-exceeding funding (BEF). This model is more suitable for binary outcomes and facilitates the

calculation of odds ratios (OR), which indicate the likelihood of exceeding the benchmark in relation to the predictor variables. The following specification is used:

$$BEF_{j,t} = \beta_0 + \beta_1 \text{fundraising cadence}_{j,t} + \beta_2 \text{serial entrepreneurship}_{j,t} + \beta_3 \text{startup age}_{j,t} + \beta_4 \text{single lead investor}_{j,t} + \beta_5 \text{industry}_{j,t} + \beta_6 \text{funding stage}_{j,t} + \varepsilon_{j,t} \quad (3)$$

We present the results of the Logit regression in Table 9, and report odds ratios. Where values above one represent increased odds, and values below one represent decreased odds of the outcome occurring. Based on the findings of the initial model in column 1, we find no significant relationship between fundraising cadence and the probability of exceeding stage-specific industry benchmarks ($\beta = 0.991$). Serial entrepreneurship has no considerable effect on benchmark outperformance ($\beta = 0.908$) either, suggesting that quicker fundraising and founder experience do not lead to better relative funding outcomes. Given the slight reduction in odds, below 1% per additional month, the practical implications of fundraising cadence on relative funding performance are minimal. This indicates that, despite faster rounds observed in the previous survival models, the quality of funding outcomes measured as exceeding industry benchmarks is not enhanced by faster pace or founder experience.

Insert Table 6 about here

Notably, startup age emerges as a consistent and statistically significant predictor for BEF ($\beta = 0.742$). Suggesting that each additional year that a startup matures reduces the odds of exceeding the industry-stage benchmark by approximately 25.8%. This implies that younger startups are more likely to raise funding that exceeds their industry-stage benchmark, potentially

due to heightened investor sentiment or perceived upside potential in early growth-stage ventures. The stage-specific robustness tests (columns 2 to 4) confirm that this pattern persists uniformly across all funding stages, with startup age repeatedly showing significant negative effects, underscoring the fact that younger startups consistently outperform benchmarks. Interestingly, fundraising cadence becomes marginally significant in the B to C transition ($\beta = 0.980$), indicating that a minor negative correlation between time lag and benchmark outperforming may be present at this stage. However, this effect is not consistent across stages.

A final robustness test utilizing an outlier-trimmed dataset (column 5), confirms the stability of the main findings. Even after removing outliers above the 99th percentile, fundraising cadence and serial entrepreneurship do not serve as significant predictors for BEF. Startup age still demonstrates a strong significant negative impact ($\beta = 0.744$). Overall these results highlight that startup age, rather than cadence or serial entrepreneurship, is the most consistent predictor of benchmark-exceeding funding.

5. Discussion and conclusion

The dynamics of startup financing have evolved rapidly, with venture capital playing a central role in shaping the access to funding, survival rates, and growth trajectories of early-stage firms. In this context, timing has emerged as a subtle yet powerful factor in fundraising strategies, influencing not just when startups raise external capital but also how much they raise and especially under what conditions. Serial entrepreneurship, as a distinct founder characteristic, for instance, has received a lot of attention from academics. It is widely known as a prominent signal that reduces information asymmetry, represents investor trust, increases access to external funding, and the perceived quality of the venture (Banerji & Reimer, 2019; Lafontaine & Shaw, 2014; Parker, 2012; Zhang, 2011). Two critical dimensions of VC

fundraising, however, remain underexplored: (i) fundraising cadence, or the timing between funding rounds, as a strategic factor which influences funding outcomes, and (ii) the interaction between fundraising cadence and serial entrepreneurship, and whether the relationship between the two shapes funding outcomes and success.

This paper addresses these gaps by investigating how fundraising cadence affects funding growth and the likelihood of outperforming industry benchmarks. By connecting fundraising cadence, serial entrepreneurship, startup age, and funding outcomes, our results show that faster fundraising cadence positively affects funding growth, and that serial entrepreneurs raise follow-on funding rounds faster than their first-time counterparts, a finding that is in line with Zhang (2011). However, as further analyses show, serial entrepreneurs do not raise larger amounts or exceed industry-specific median benchmarks. The only consistent predictor of beating industry-specific benchmarks is startup age.

Taken together, these results reveal a critical distinction: while serial entrepreneurs consistently achieve faster funding rounds, as evidenced by the survival models, this speed does not result in higher funding growth or improved benchmark performance. In fact, the effect of fundraising cadence, particularly in later growth stages, suggests that decision-makers should not necessarily equate quick capital access with enhanced funding quality.

5.1 Theoretical implications

This study positions fundraising cadence as a strategic lever in venture financing, which reflects more than just operational timing. The empirical results show that longer intervals between funding rounds are associated with higher funding growth, particularly in early and mid-growth-stage transitions. This parallels both startup lifecycle theory and staged financing theory, which emphasize that capital is often released in tranches tied to key milestones (La Rocca et al.,

2011; Talmor & Cuny, 2005). Additionally, VC investors making decisions on potential investments within the highly dynamic VC industry often do not have the luxury of waiting for better startups to invest in. These small temporal shifts, such as delaying funding rounds by even one or two months, can offer critical time for startups to strengthen KPIs, market traction, or signal overall greater readiness to VC investors. In turn, this allows founders to enter negotiations with greater leverage, which may attract larger follow-on rounds. In fact, the finding that a one-month delay in fundraising cadence is associated with a 5.6% increase in funding growth underscores that cadence is not just reactive to performance but may actually be proactively managed to strengthen outcomes.

The role of serial entrepreneurship further deepens this observed dynamic. As expected, serial entrepreneurs raise follow-on rounds significantly faster than first-time founders do. Additionally, unlike Zhang (2011), who documents the significant speed advantage of serial entrepreneurs using a dataset of Chinese venture-backed startups, this study examines U.S. startups. This new geographic perspective confirms that serial entrepreneurs secure funding rounds more quickly across different market environments, adding to the broader generalizability of this speed advantage finding.

This supports the view that entrepreneurial experience is a credible signal that reduces information asymmetry and speeds up investor decision-making during the fundraising process. However, this speed advantage does not translate into better funding outcomes, as serial entrepreneurs do not raise significantly larger rounds, and do not showcase higher odds of exceeding industry benchmarks. This introduces a potential signaling paradox: while speed may impress investors, it also might neglect any strategic benefits of waiting, like a stronger market positioning or improved milestone validation.

In other words, while experience from prior ventures helps founders and their firm to raise money faster, it can also lead them to move too quickly before reaching critical milestones. This is especially important in later funding stages, where traction and performance metrics seem more important than founder experience. Thus, speed may be an overrated proxy for quality. Moreover, if the next funding round follows too soon, the startup may not have had enough time to show real progress, making it more difficult to justify higher valuation and capital infusions.

Startup age, or a firm's maturity, emerges as the only consistent significant variable predicting survival likelihood and benchmark-exceeding funding. This provides empirical support for theoretical insights from startup lifecycle theory to signaling theory. Consistent with lifecycle-based views of financing, older startups tend to progress more slowly through funding rounds. This finding aligns with the belief that investor expectations evolve as startups mature, more particularly that younger firms often benefit from novelty-driven narratives, while financial performance, market traction, and other quantifiable metrics gain more significance for older firms. This shift is further seen in signaling theory, where novelty, hype, and the young age of startups can serve as a signal of innovation or disruptive potential, while maturity demands higher proof of sophistication.

Next to slowing fundraising cadence, startup age also reduces the likelihood of exceeding industry-specific funding benchmarks. This suggests that as firms mature, they may still raise substantial rounds, but less frequently outperform peers within their industry and stage. Importantly, startup age does not show a significant effect for funding growth, which indicates that older firms do not tend to raise more capital relative to previous rounds. Together, these findings reveal a double-edged dynamic in fundraising cadence that suggests that maturity may be able to boost credibility, yet also may slow down the funding cycle, making it harder for older

firms to stand out in competitive funding environments. This may give a deeper glimpse into how VC investors make decisions and that they often back younger firms based on potential and vision, while later-stage investors follow stricter criteria, emphasizing strong financial metrics and proven business models. As a result, mature startups face longer validation cycles or face higher thresholds and need to achieve greater milestones to exceed market expectations.

Lastly, technology sub-sector industry differences are found to not play any role in shaping fundraising cadence or outcomes. Stage effects however do play a clear role. Startups raising earlier rounds move faster through funding cycles and raise follow-on rounds more quickly. They additionally experience higher funding growth, likely due to more flexible investor expectations and milestone-driven urgency. These findings reinforce the relevance of startup lifecycle dynamics, especially the pace and magnitude of fundraising as firms mature.

5.2 Practical implications for founders and investors

By reframing fundraising cadence and timing as a strategic lever rather than a passive indicator of momentum, this study provides important insights for founders, venture capitalists, and other financing decision-makers. To begin with and rather than treating the time between funding rounds as a fixed or externally driven outcome, founders can actively manage fundraising cadence to shape investors' perceptions, improve valuation leverage, and optimize funding outcomes. The findings of this study suggest that startups benefit from completing meaningful milestones before raising the next round. This underscores the logic of staged financing theory, where capital infusions are based on performance, and indicates that well-timed funding rounds and slight delays of even one or two months may significantly enhance a startup's negotiating position and lead to larger follow-on funding.

In addition, the results indicate that serial entrepreneurs may benefit from their ability to raise faster, yet an increased pace does not guarantee better outcomes. Therefore, serial entrepreneurs should resist the temptation to rely solely on reputation-driven momentum and instead engage in strategic pacing with meaningful business progress. This is especially critical in later stages, where existing research suggests that investors increasingly rely on traction and financial metrics over founder background (Gompers & Lerner, 2001; Hsu, 2007). Furthermore, founders, regardless of their background, should balance the urgency of securing funding with the strategic value of timing, realizing cadence as a tool for shaping the funding trajectory of the firm.

From an investor's perspective, the findings cast doubt on common assumptions about speed as a signal. Fast-paced rounds could be a sign of recent momentum, market interest or founder skill and background. However, they may also lead to underdeveloped business strategies, reduced negotiating power, rushed decision making and valuation risk. Thus, investors should carefully weigh the pace of fundraising with respect to how startups have used the gap between rounds and if that time was used to purposefully improve strategic positions.

At a broader decision-making level, financing decision-makers, including investors, advisors, and board members, should reevaluate their interpretations of fundraising cadence. This study shows that faster cadence does not necessarily signal higher quality or better outcomes, particularly as startups mature. Evaluating fundraising cadence, relative to stage, milestone achievement, and startup maturity, can support more accurate assessments of startup quality by considering what the timing of a funding round reflects in terms of readiness and milestone achievement.

5.3 Limitations and directions for future research

Despite the theoretical and practical implications that have been discussed, several limitations remain that warrant additional investigation. First, the dependent variables used, namely funding growth and benchmark-exceeding funding, provide helpful but imperfect proxies for fundraising performance or success. Small base values in early rounds could inflate growth percentages, while marginal and extreme funding exceedance values are treated equally by the benchmark dummy variable. Future research could adopt percentile-based funding metrics, continuous measures of benchmark-exceedance, or further measures to capture funding outcomes more precisely.

Second, the study relies on publicly available data from Tracxn, Crunchbase, and Gain.pro. Despite manual verification, data collected from these platforms may still contain reporting inconsistencies or gaps, especially regarding funding dates or investor roles. This poses limits on data granularity and could negatively impact the accuracy and granularity of fundraising cadence.

Third, the sample is restricted to U.S.-based technology startups between Series A to D. This focus limits the generalizability to other industries, geographies, and financing stages. Seed rounds, as well as later-stage rounds or exit phases such as IPOs and acquisitions, are not taken into consideration. Future research could expand the scope and further examine how fundraising cadence and outcomes evolve over the full startup lifecycle. The industry focus within the technology sector, which was chosen for data availability, also narrows the context. Further research may include sectors outside of technology to widen it to sectors with different capital intensity, product cycles, or risk profiles, such as healthcare, industrials, and more. Comparing and analyzing these differentiating sectors could help uncover if the fundraising cadence patterns identified in this study are tech-specific or might be shaped by broader industry dynamics.

In addition, there are various other qualitative variables such as investor reputation, board pressure, and other elements that may have a significant impact on fundraising cadence, yet remain outside of the scope of this quantitative design. Furthermore, this study does not account for temporal shocks or macroeconomic cycles, which could affect the funding pace. Similarly, only startups that progressed to all rounds from A to D were selected, limiting the survival model as no right-censoring is present. As a likely result, only survivors may have been selected, which limits the statistical robustness of the Cox proportional hazards model.

Beyond previously discussed limitations, future research may also explore new conceptual avenues. One promising direction involves further analyzing the mechanisms behind the observed relationships of this study, namely, why serial entrepreneurs raise faster, and why compressed fundraising cadence does not translate to better outcomes. Behavioral research can additionally benefit by exploring the extent to which fundraising cadence is shaped by milestone achievement or strategic readiness and if external pressure plays a role in this dynamic. These questions also apply to investors, whose decision-making timelines, fund pressures from Limited Partners (LPs), or evaluation heuristics may have a significant impact on fundraising cadence. Shifting the focus to investor-side dynamics, including the role of LP pressure, VC fund cycles, external deadlines, or co-investor coordination, could extend the concept of fundraising cadence beyond the startup level and into the broader VC ecosystem.

Ultimately, this paper introduces a novel perspective that considers fundraising cadence and timing as critical elements within VC fundraising dynamics. Correspondingly, the outlined analysis lays the groundwork for future research to further explore how temporal patterns interact with investor behavior, startup growth trajectories, and capital allocation strategies. As such, it is important to examine fundraising cadence not just as a byproduct of growth, but rather

as a strategic lever, consistent with staged financing and signaling theory frameworks, that can shape funding outcomes across stages, sectors, and founder types.

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Tables and figures

Table 1 Descriptive statistics of funding rounds

Variable	Description	Mean	Median	SD	Min	Max
Fundraising Cadence	Months between funding rounds	20.01	17	13.22	0	122
Funding Growth	Relative increase in funding rounds (% growth)	1.94	1.2	5.71	-0.75	143
Benchmark-Exceeding Funding (BEF)	Share of rounds exceeding benchmark funding	77.20%	1	-	0	1
Funding Amount	Total funding amount raised (in \$K)	40.47	21	66.14	1	850
Benchmark Median	Industry-stage median benchmark (in \$K)	15.71	15.16	9.16	4	32
Serial Entrepreneur	Share was founded by serial founders	63.50%	1	-	0	1
Startup Age	Age of firm (in years)	12.39	12	3.8	6	26
Single Lead Investor	Share of rounds led by a single investor	8.60%	0	-	0	1

Table 2 Descriptive statistics by funding transition

Variable	Mean	Median	SD	Min	Max
<i>panel a</i> Transition from Series A → B					
Fundraising Cadence	18	16	11	3	62
Funding Growth	3	2	10	-0.5	143
Benchmark-Exceeding Funding	79%	1	41%	0	1
Funding Amount	22	9	83	1	850
Serial Entrepreneur	64%	1	48%	0	1
<i>panel b</i> Transition from Series B → C					
Fundraising Cadence	21	18	14	0	88
Funding Growth	2	1	2	-0.5	11.5
Benchmark-Exceeding Funding	74%	1	44%	0	1
Funding Amount	30	23	28	2.2	300
Serial Entrepreneur	64%	1	48%	0	1
<i>panel c</i> Transition from Series C → D					
Fundraising Cadence	21	18	15	3	122
Funding Growth	1	1	2	-0.75	12.3
Benchmark-Exceeding Funding	79%	1	41%	0	1
Funding Amount	69	50	64	6	450
Serial Entrepreneur	64%	1	48%	0	1

Note: A one-way ANOVA was conducted to assess whether mean differences across the three round transitions (A→B, B→C, C→D) were statistically significant. The test revealed significant differences in funding amounts ($F = 43.36$, $**p < 0.01$), timing between rounds ($F = 4.59$, $p = 0.01$), and funding growth ($F = 7.31$, $**p < 0.01$), while success rates did not differ significantly ($F = 0.86$, $p > 0.1$). Serial Entrepreneur values are consistent across stages, as founder type does not vary within a startup.

Table 3 Descriptive statistics by founder type

Variable	Serial Entrepreneur (n=168)		First-Time Founder (n=98)		t -statistic
	Mean	Median	Mean	Median	
Fundraising Cadence	19.15	16	21.52	19	2,49 **
Funding Growth	2.02	1	1.81	1	-0.57
Benchmark-Exceeding Funding	74%	1	83%	1	3,00***
Funding Amount	40.58	20	40.26	23	-0.07
Startup Age	12.93	12	11.44	11	-6,29***
Single Lead Investor	9%	0	9%	0	-0.04

Note: Reported Values reflect t-statistics from two-sample t-tests comparing Serial and First-Time founders. Significance levels:

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4 Survival analysis

Variable	(1)	(2)	(3) A → B	(4) B → C	(5) C → D
Serial Entrepreneurship	1.356*** (0.076)	0.4*** (0.371)	1.261* (0.132)	1.565*** (0.137)	1.281* (0.134)
Startup Age	0.917*** (0.011)	0.838*** (0.029)	0.922*** (0.02)	0.902*** (0.022)	0.914*** (0.019)
Serial Entrepreneurship * Startup Age		1.109*** (0.031)			
Single Lead Investor	0.996 (0.131)	0.997 (0.131)	1.004 (0.161)	1.296 (0.332)	0.908 (0.336)
Industry: Enterprise Applications	0.871 (0.151)	1.123 (0.153)	0.887 (0.275)	0.977 (0.261)	1.241 (0.267)
Industry: FinTech	0.939 (0.152)	0.906 (0.111)	0.778 (0.191)	0.836 (0.199)	1.239 (0.196)
Industry: HealthTech	0.813 (0.159)	0.881 (0.122)	0.863 (0.215)	0.723 (0.213)	0.952 (0.214)
Industry: High Tech	0.984 (0.17)	0.974 (0.139)	1.269 (0.242)	0.939 (0.236)	0.952 (0.242)
Industry: Others	0.933 (0.149)	0.976 (0.106)	0.944 (0.183)	0.812 (0.184)	1.233 (0.189)
Stage: B → C	0.783*** (0.09)	0.772*** (0.09)			
Stage: C → D	0.775*** (0.09)	0.768*** (0.09)			
Observations	798	798	266	266	266
Concordance	0.609	0.615	0.605	0.613	0.598
Log-rank p-value	<0.001	<0.001	0.001	<0.001	<0.001

Note: Reference stage category for Models 1 and 2 is Series A to B. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Concordance approximates predictive accuracy.

Table 5 Funding growth

Variable	Full Sample		Outliers Removed	
	(1)	(2)	(3)	(4)
Fundraising Cadence	0.056*** (0.016)	0.018 (0.028)	0.023*** (0.005)	0.017** (0.008)
Serial Entrepreneur	0.327 (0.428)	0.116 (1.867)	-0.007 (0.123)	-0.503 (0.535)
Startup Age	-0.052 (0.057)	0.016 (0.155)	-0.018 (0.017)	-0.042 (0.044)
Fundraising Cadence x Serial Entrepreneur		0.056* (0.034)		0.02 (0.047)
Serial Entrepreneur x Startup Age		-0.081 (0.165)		0.027 (0.047)
Single Lead Investor	2.443*** (0.732)	2.407*** (0.732)	0.562*** (0.222)	0.561*** (0.212)
Industry: EdTech	-0.33 (0.845)	-0.322 (0.853)	-0.08 (0.242)	-0.048 (0.245)
Industry: Enterprise Applications	0.47 (0.617)	0.426 (0.619)	-0.368** (0.178)	-0.385** (0.179)
Industry: HealthTech	-0.447 (0.681)	-0.435 (0.682)	-0.048 (0.196)	-0.037 (0.196)
Industry: High Tech	-0.196 (0.762)	-0.144 (0.763)	-0.211 (0.17)	-0.175 (0.179)
Industry: Others	-0.19 (0.59)	-0.171 (0.59)	-0.214 (0.17)	-0.214 (0.17)
Stage: B → C	-1.308*** (0.50)	-1.283** (0.50)	-0.464*** (0.144)	-0.460*** (0.144)
Stage: C → D	-1.568*** (0.499)	-1.568*** (0.499)	-0.748*** (0.144)	-0.748*** (0.144)
Intercept	2.066** (0.859)	2.101 (1.756)	1.875*** (0.247)	2.269*** (0.503)
Reference Stage	A → B	A → B	A → B	A → B
Observations	798	798	790	790
Adjusted R ²	0.036	0.037	0.069	0.062

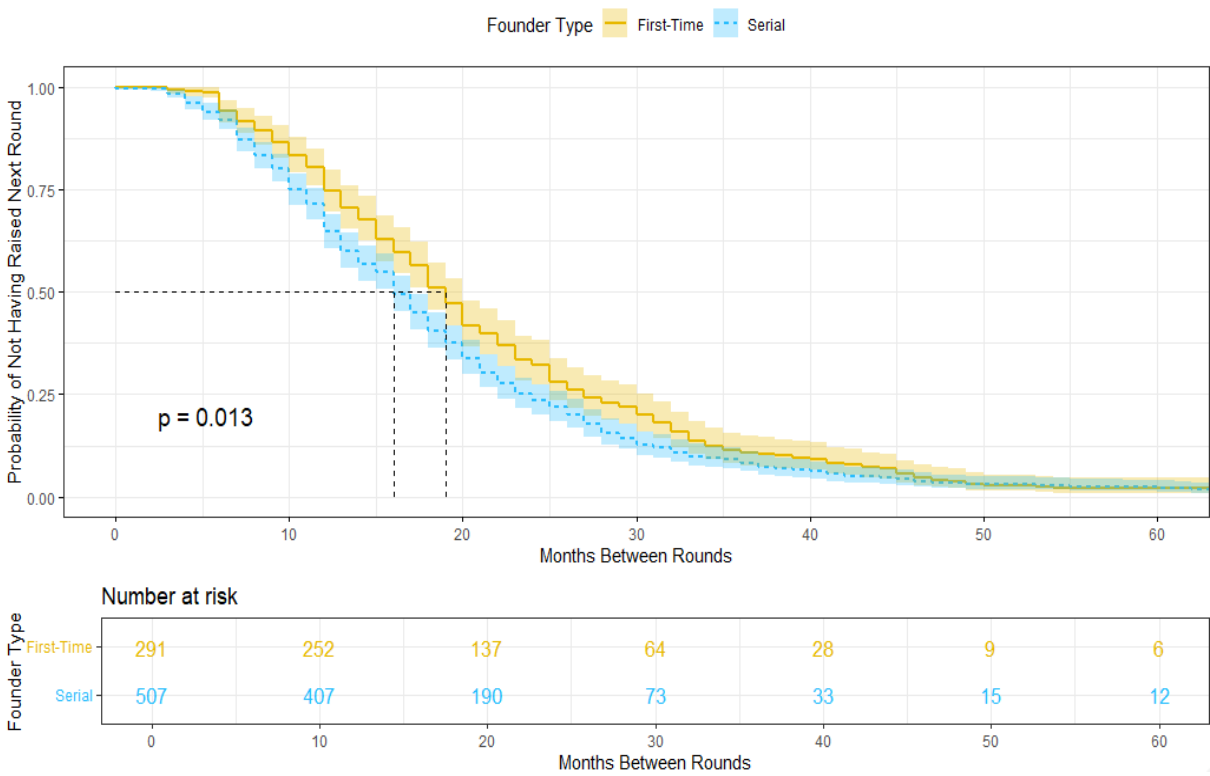
Note: Reference industry is Fintech. Standard errors are shown in parentheses, Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Table 6 Benchmark exceeding funding

Variable	Full Sample				Outliers Removed
	(1)	(2) A → B	(3) B → C	(4) C → D	(5)
Fundraising Cadence	0.991 (0.007)	0.990 (0.015)	0.980* (0.011)	1.007 (0.012)	0.992 (0.007)
Serial Entrepreneur	0.908 (0.216)	1.242 (0.371)	0.810 (0.363)	0.697 (0.411)	0.915 (0.218)
Startup Age	0.742*** (0.03)	0.773*** (0.049)	0.744*** (0.051)	0.684*** (0.062)	0.744*** (0.03)
Single Lead Investor	0.584* (0.323)	0.615 (0.405)	0.364 (0.713)	0.598 (0.809)	0.579* (0.33)
Industry: EdTech	0.883 (0.361)	1.126 (0.622)	0.971 (0.622)	0.668 (0.64)	0.836 (0.363)
Industry: Enterprise Applications	1.711* (0.311)	1.988 (0.526)	1.275 (0.519)	2.553 (0.606)	1.701* (0.318)
Industry: HealthTech	0.858 (0.327)	1.063 (0.556)	0.771 (0.561)	0.808 (0.61)	0.814 (0.33)
Industry: High Tech	1.274 (0.371)	0.804 (0.581)	1.331 (0.641)	2.458 (0.752)	1.289 (0.379)
Industry: Others	1.059 (0.294)	1.826 (0.525)	0.944 (0.497)	0.746 (0.536)	1.043 (0.299)
Stage: B → C	0.707 (0.241)				0.637* (0.246)
Stage: C → D	0.949 (0.248)				0.864 (0.253)
Intercept	240.635*** (0.486)	98.134*** (0.764)	261.560*** (0.801)	590.171*** (0.904)	260.495*** (0.494)
Reference Stage	A → B	None	None	None	A → B
Observations	798	266	266	266	790
Pseudo R ²	0.198	0.164	0.205	0.264	0.198

Note: Reference industry = Fintech. Estimates are shown as odds ratios with standard errors in parentheses. column (5) uses a trimmed version of the growth variable in the dataset, that removed outliers above the 99% threshold (11.5x). Estimates are not directly comparable across models due to differences in sample composition. Significance levels: *** p < 0.01, ** p < 0.05, * p < 0.1.

Figure 1 Kaplan-Meier curves by founder type



Appendix

Table A.1. List of variables

Variable	Description	Construction Method
Fundraising Cadence	Months between two subsequent VC rounds	Derived from the difference in months between adjacent round dates
Funding Growth	Percentage change in funding between two successive rounds	Calculated as the change in capital raised between two successive rounds
Benchmark-Exceeding Funding (BEF)	Binary indicator for whether funding raised exceeded the industry-specific median	Determined by comparing the raised funding amount to Tracxn's sub-sector and stage-specific median benchmarks
Funding Amount	Total amount raised in each funding round (in \$K)	Sourced from Tracxn, Gain.pro, or Crunchbase Manually verified via Tracxn, Crunchbase, and LinkedIn.
Serial Entrepreneur	Binary indicator of whether the startup was founded by a serial entrepreneur	Coded as 1 for serial entrepreneurs, 0 for first-time founders
Startup Age	Age of firm (years)	Calculated as 2025 minus the founding year
Single Lead Investor	An indicator of whether a single lead investor participated	Coded as 1 if only one lead investor was listed; 0 otherwise
Industry	Startup's tech sub-sector classification	Based on Tracxn's categories: FinTech, HighTech, EdTech, Enterprise Applications, HealthTech, and Others
Funding Stage	Binary indicator if funding round was Series A, B, C, or D	Sourced from Tracxn, Gain.pro, or Crunchbase, binary coded