

Decoding Startup Valuation: The Interplay of Founder, Firm, Industry, and Investor Dynamics

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Certificate Of Original Authorship

I, Haritha Veeramanickathadathil Hari, declare that this thesis, is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the UTS Business School at University of Technology Sydney.

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I certify that the work in this thesis has not previously been submitted for a degree, nor has it been submitted as part of the requirements for a degree except as fully acknowledged within the text. This thesis is the result of a Collaborative Doctoral Research Degree program with Indian Institute of Technology Madras (IITM), Chennai, India. This research was supported by an Australian Government Research Training Program (RTP) Scholarship doi.org/10.82133/C42F-K220.

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Dedication

Dedicated to

all the parents who choose to open doors they never got to walk through!

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Abstract

Startup valuation is a complex yet critical dimension of entrepreneurial finance, shaping ownership structures, funding negotiations, and stakeholder expectations. For decades, venture capital (VC) investors and researchers have debated whether startup success hinges more on the *jockey* (the founder) or the *horse* (firm performance). This thesis extends the discussion by introducing the *Jockey-Horse-Meadows-Trainer* framework, which integrates industry attractiveness (*the meadows*), and investor behavior (*the trainer*) into the valuation dynamics.

Drawing on a dataset of Indian startups founded between 2000 and 2020 and funded by venture capital investors, this study explores four key questions: (1) How do founder characteristics and financial indicators shape the growth of startup valuations? (2) To what extent does industry attractiveness affect firm valuation, and how is this relationship moderated by the startup's financial health? (3) How does venture capital investor overconfidence influence startup valuations, and is this effect moderated by syndication among investors? (4) What firm-level and macro-level factors determine access to VC funding?

This study reframes startup success as a dynamic, continuous process by modeling it as the probability of achieving higher post-money valuations across successive funding rounds using binomial options framework, to capture the evolving nature of startups' growth trajectory. Considering that the probability of success is a range bound dependent variable, firm-level factors that signals valuation growth has been analysed using beta regression. The study further employs SHAP (SHapley Additive exPlanations) analysis which adds valuable interpretability by quantifying the contribution of each factor to the predicted probability. To uncover the role of industry environment on startup valuation, an Industry Attractiveness (*IA*) index was developed and its relationship with valuation was analysed using a cubic regression model and spline regression plot. The influence of VC investor behaviour on startup valuation is assessed by constructing an Overconfidence (*OC*) index, which is analysed using regression models and illustrated through a kernel density plot to show its distribution. Additionally, the study looked beyond valuation to identify the drivers of VC funding through a fixed effects panel regression and variable importance analysis using a multi-layer perceptron neural network model.

The results analysing success probability drivers indicate that financial leverage, liquidity, and operating efficiency indicators outweigh founder traits for scaling startup valuations. Interestingly, a higher debt-to-equity ratio is positively associated with valuation growth, suggesting that prudent use of debt financing enhances startups' capacity to scale. Moreover, the interaction between founder pedigree and financial performance is strongest in intermediate stages but weakens later, suggesting a pivot from narrative-based signals to performance-based evidence.

Industry conditions in which the startups operate add another layer of complexity. Contrary to assumptions that more attractive industries always boost valuations, the results highlight a non-linear, reverse S-shaped pattern. This indicates that moderate improvements in industry

attractiveness tend to support higher startup valuations, but at very high levels of attractiveness the benefits taper off. Industries that are “too attractive” becomes crowded, competitive, or overheated, thereby reducing the marginal advantage to individual startups. Moreover, the results indicate that VCs prioritize signals and treat them as substitutes rather than additive drivers of valuation. Hence, strong firm fundamentals compensate for unattractive industry contexts in driving valuation.

Investor psychology further shapes the valuation dynamics. The empirical analysis finds that overconfident investors tend to assign inflated valuations beyond what fundamentals justify, creating pockets of mispricing. However, syndication, where multiple investors co-invest, acts as a counterbalance. The shared due diligence and collective risk temper individual biases, moderates the extent of overvaluation.

Beyond explaining valuation trajectories, the research clarifies whether the factors that drive valuations similarly determine the actual funding amounts secured. Financial discipline remains central to both valuation growth and funding access, but softer founder signals such as premier institute education carry greater weight in attracting initial funding than in sustaining long-term valuation increases. This divergence underscores the need for cautious reliance on reputation-based cues that may not align with the measurable performance required for sustained value creation.

By combining robust econometric techniques with advanced data-driven methods, this study offers a practical roadmap for decoding valuation dynamics in real-world contexts. For entrepreneurs, it provides clear guidance on balancing credible founder signals with strong financial fundamentals to build investor confidence and move beyond initial stages. For venture capital investors, these findings highlight the importance of adopting a more disciplined approach to screening, deal structuring, and valuation that integrates founder attributes, firm performance, industry prospects, and behavioral factors. For policymakers, the study provides useful pointers for designing support measures that go beyond industry trends, strengthen firm-level capabilities, promote responsible investor practices, and tailor policies with the specific needs of an emerging startup ecosystem. For researchers, this work stands out as an early attempt to capture the complex interplay of factors shaping startup valuation in an emerging market context, opening avenues for deeper exploration in entrepreneurial finance.

Keywords: *Startup Valuation; Venture Capital Funding; Founder Characteristics; Financial Performance; Industry Attractiveness; Investor Overconfidence; Emerging Market*

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List of abbreviations

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
EBIT	Earnings before interest and taxes
IA	Industry attractiveness
IPO	Initial public offerings
M&A	Mergers & acquisitions
MBV	Market based view
MLP	Multi-layer perceptron
OC	Overconfidence
OLS	Ordinary least square
p	Risk-neutral success probability
RBV	Resource based view
ROIC	Return on invested capital
SHAP	Shapley Additive Explanation
VC	Venture capital

Chapter 1

Introduction

1.1 The growing startup ecosystem

As Paul Marsden, a former British writer, aptly put it, “*Business is all about solving people’s problems – at a profit.*” Startups are built on this very principle. They tackle real-world problems with fresh, often disruptive solutions that grow, adapt, and generate returns along the way. In other words, startups turn bold ideas into scalable ventures. They challenge traditional business models by pushing the boundaries of technology, services, and customer experience (Lerner and Nanda, 2020).

While there is no universally agreed-upon definition, startups are typically understood as newly established ventures that aim to solve market problems through novel products, services, or business models. These ventures are generally structured as private limited companies or limited liability partnerships. They are frequently supported by external funding from sources such as angel investors, venture capital firms, incubators, or government grants (Berre and Le Pendeven, 2023). Many startups begin with a small founding team and lean operational models, relying heavily on digital tools, agile processes, and iterative development (Corea et al., 2021). Their organizational structures are often flat and flexible, enabling faster decision-making and adaptability compared to large, hierarchical firms.

The significance of startups extends far beyond their individual business outcomes. These ventures serve as engines of innovation, economic growth, and job creation (Bonini and Capizzi, 2019). In many cases, startups challenge incumbents and legacy firms by offering better, cheaper, or more efficient alternatives (Nanda et al., 2020). On a broader scale, startups

contribute to national competitiveness in the global economy and help shape future markets. For instance, in India, fintech startups have been instrumental in driving the success of the Unified Payments Interface (UPI), a platform that revolutionized digital payments. Beyond convenience and ease of payment, this innovation has significantly advanced financial inclusion, bringing secure, real-time banking to millions who were previously underserved. What began as a startup-driven initiative has now positioned India as a global leader in digital finance and inclusive innovation.

The last three decades have witnessed an unprecedented surge in attention toward the startup landscape, fuelled by the rise of high-growth ventures and the expanding reach of venture capital. The emergence of ‘*unicorns*’, privately held startups with valuations exceeding one billion dollars, symbolizes the bold risks and rewards that define the modern entrepreneurial ecosystem. Record-breaking funding rounds, increasing cross-border investments, and the rapid expansion of startup hubs around the world have increased the glam of being associated with an entrepreneurial ecosystem.

The allure of becoming the next big tech founder draws many into the startup world. While the glamour of celebrated startup success stories is undeniable, the journey of entrepreneurship is far from a cakewalk. Unlike established firms, startups operate in highly uncertain environments, where rapid experimentation and risk-taking are central to survival (Bustamante et al., 2021). Limited financial resources, lean teams, and regulatory constraints further amplify their vulnerability. Technological risks, shifting customer preferences, and intense competition from both incumbents and other startups add additional layers of uncertainty (Bradley et al., 2019). These factors make the early years of a startup especially precarious, with a high likelihood of failure. Surviving and scaling the business in this volatile landscape requires agility, resilience, and the ability to continuously adapt. This ability to navigate ambiguity and capitalize on emerging opportunities is what allows startups to challenge incumbents and

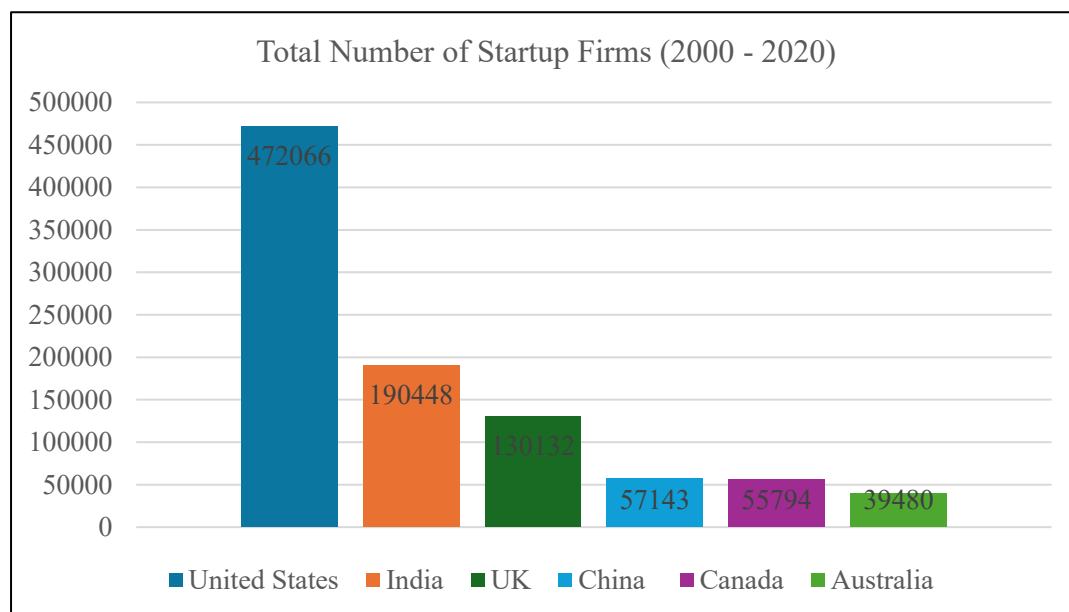
disrupt industries. However, this very nature also makes them prone to volatility and steep challenges, where the line between breakthrough and breakdown is often razor-thin.

1.2 Startup landscape in India

According to the Economic Survey 2021-22, India is the third-largest startup ecosystem after the United States and China. The total funding from 2014 to 2021 amounts to \$1.1 trillion in the US, followed by \$624 billion in China and \$112 billion in India. When it comes to the total number of startup firms established in the respective countries from 2000 to 2020, India surpasses the UK and China and stands in second place after the US. As indicated in Figure 1.1, the United States leads the trend with 472,066 firms, followed by India (190,448 firms) and the United Kingdom (130,132 firms).

Figure 1.1 Distribution of startup firms in the world's six leading startup hubs

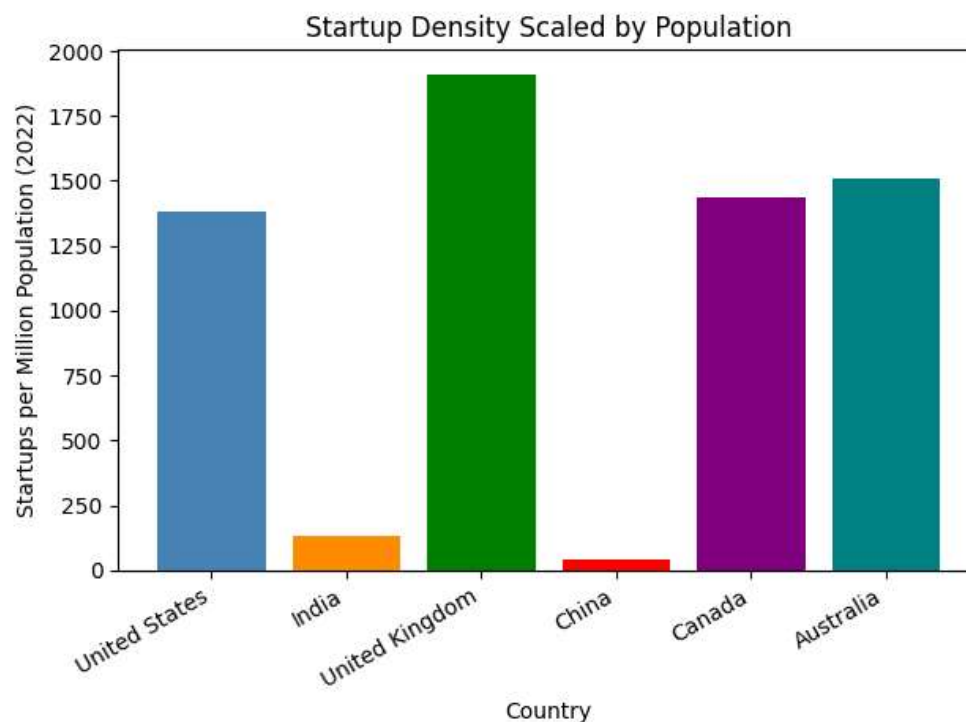
This figure presents the total number of startup firms founded in the six countries with the highest number of startups - the United States, India, the United Kingdom, China, Canada, and Australia, during the period 2000–2020. The data is sourced from Tracxn and highlights where new venture creation has been most concentrated over the past two decades.



While Figure 1.1 presents absolute startup counts, such comparisons may be influenced by differences in population size across countries. Larger economies are likely to exhibit higher startup volumes simply due to scale. To enable a more meaningful cross-country comparison, startup activity is therefore scaled by population. Figure 1.2 reports the cumulative number of startups founded per million inhabitants during 2000–2020 across the six leading startup hubs. Once startup activity is adjusted for population, the relative rankings change noticeably. Countries such as the United Kingdom, Canada, and Australia exhibit higher startup density compared to India and China. Despite India’s strong performance in absolute startup counts, its startup intensity remains lower when population size is taken into account. This highlights the distinction between startup volume and startup concentration across countries.

Figure 1.2 Startup density scaled by population

This figure presents the cumulative number of startups founded during 2000–2020 per million inhabitants across six leading startup hubs, scaled by 2020 population to ensure comparability across countries. Startup data are sourced from the Tracxn database, with population figures obtained from World Bank statistics.



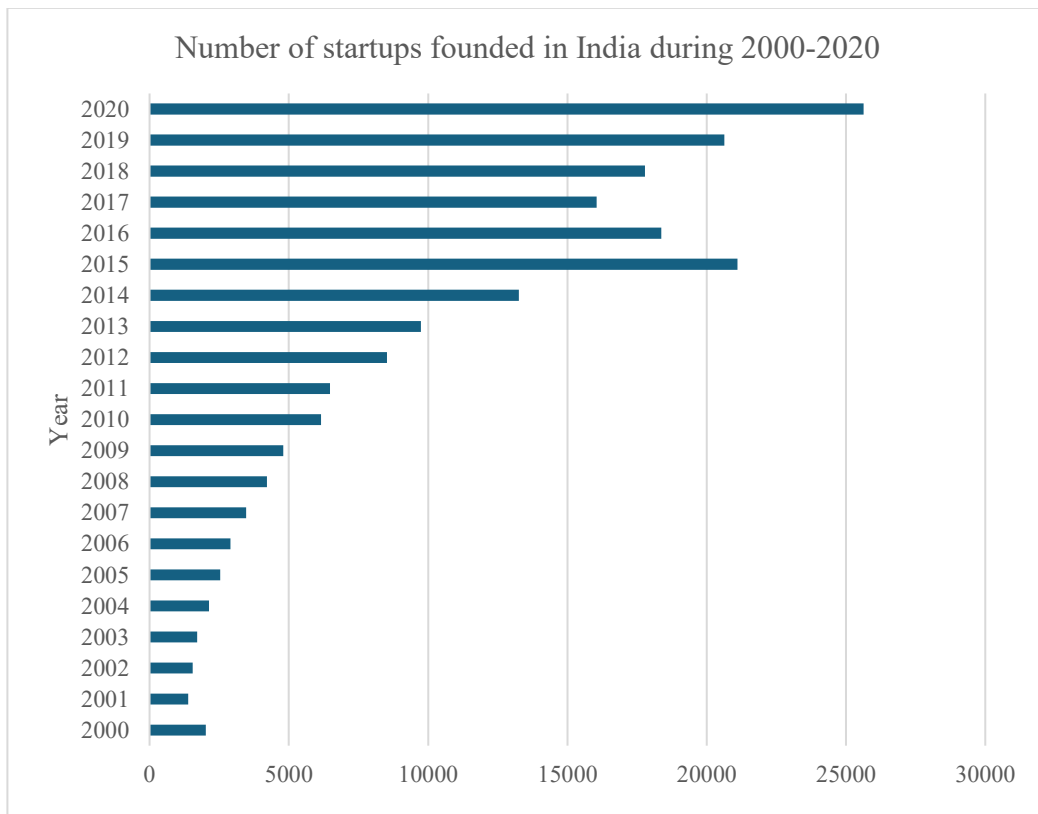
Despite lower startup density, India's scale and recent acceleration have positioned it as a key destination for venture capital (VC) investment. India ranks third in terms of the number of startups globally, with diversity across fintech, healthtech, deep-tech, and sustainability ventures. Over the last decade, there has been a thirtyfold increase in startup activity in India, accounting for 15% of its GDP growth (KPMG, 2024).

The Department for Promotion of Industry and Internal Trade (DPIIT, Government of India) states that to qualify as a startup, an entity must satisfy the following conditions;

- i. The firm has to be incorporated as a private limited company or registered as a partnership firm or a limited liability partnership in India.
- ii. Ten years have not been completed since its date of incorporation/registration.
- iii. The turnover for any financial year should not exceed INR 100 crores since the incorporation/registration.
- iv. The entity should be working towards innovation, and development, or the improvement of products, services, or processes.
- v. There must be a promising, scalable business model with the potential for employment generation or wealth creation

Figure 1.3 Year-wise distribution of the number of Indian startups

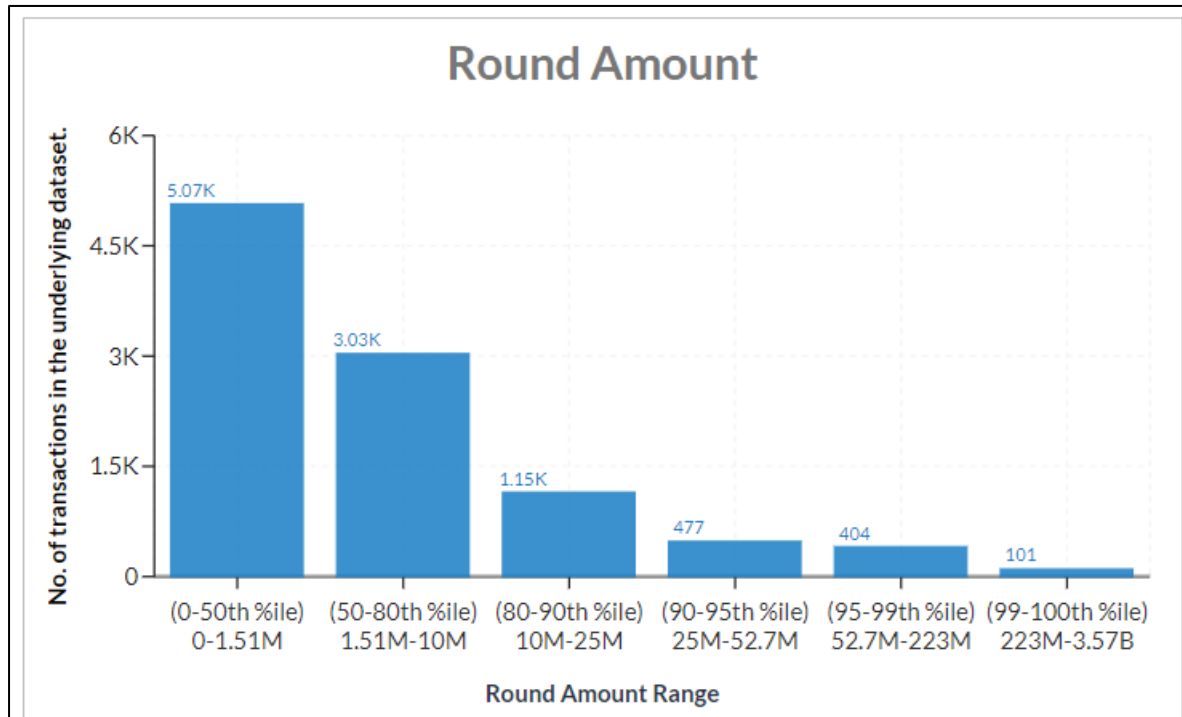
This figure illustrates the year-wise distribution of new startup firms established in India between 2000 and 2020. The data, sourced from Tracxn, highlights trends in startup formation over the past two decades and provides context for understanding the growth of India's entrepreneurial ecosystem.



The distribution of the number of startup firms established in India during the past two decades (2000-2020) is shown in Figure 1.3. As the graph indicates, even during the economic uncertainties and the onset of a global pandemic, the growth has been remarkable and persistent, with an unprecedented number of 25,628 firms.

Figure 1.4 Distribution of the funding round amount of Indian startups

This figure illustrates the distribution of startup funding rounds by investment size percentiles. The data, sourced from Tracxn, indicates that a large proportion of transactions occur within the lower funding ranges (up to USD 10 million), while only a small fraction of deals exceed USD 223 million. This distribution highlights the highly skewed nature of startup funding, where a few exceptionally large rounds account for a small share of total transactions but often attract disproportionate attention in entrepreneurial finance discussions.



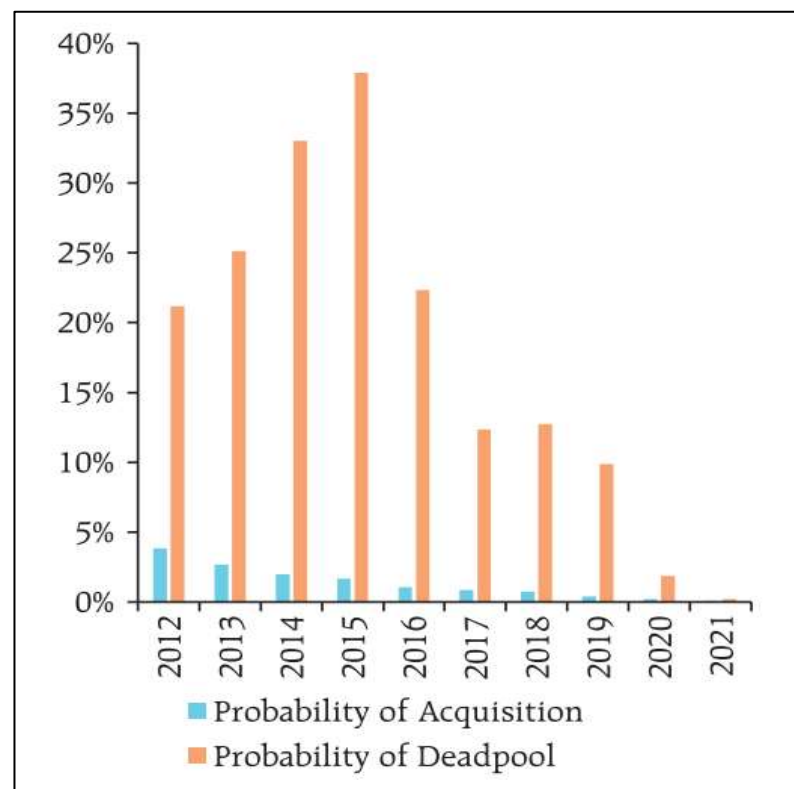
Even though the total number of firms gives a promising picture, a closer look at the funding round distribution gives us an idea of the sustenance and growth of the firms at the later levels. As shown in Figure 1.4, the number of transactions decreases as the range of round amounts increases. The lion's share of funding falls within the funding range of up to 10 million.

This uneven distribution of funding rounds points to an important aspect of the startup journey. While many ventures succeed in securing initial capital, far fewer are able to attract the larger follow-on investments needed for sustained growth and scaling. Progressing through successive funding rounds requires startups to continuously demonstrate their potential, adapt to changing market conditions, and maintain the confidence of investors. These challenges

become more pronounced as ventures move from early-stage experimentation to later-stage expansion, where the stakes and resource requirements are significantly higher.

Figure 1.5 Probability of venture outcomes for Indian startup firms (2012–2021)

This figure illustrates the annual probabilities of acquisition and closure (“deadpool”) for Indian startups between 2012 and 2021. The data from Saroy et al. (2023) shows that the likelihood of startups shutting down consistently exceeds the probability of being acquired, highlighting the inherent risks associated with entrepreneurial ventures in India.



Despite the promise they hold, more than 90% of startups fail - a statistic that is both staggering and concerning (IBM,2017). A high failure rate, as shown in Figure 1.5, highlights the need to move beyond the romanticism of entrepreneurship and delve deeper into the structural, strategic, and contextual factors that determine whether a startup succeeds or fails.

1.3 Valuation and its significance for startups

“Anything that is measured and watched, improves” – Bob Parsons, GoDaddy founder

When it comes to startups, no discussion sparks more debate and fascination than valuation. Headlines about billion-dollar ‘unicorns’ and record-breaking funding rounds capture public imagination and investor confidence alike. They highlight the bold bets investors place on ventures that embrace innovation. But beyond the headlines, valuation serves as a powerful signal. It reflects what founders, investors, and the market collectively believe about a startup’s potential to scale, disrupt, and create future value.

Valuation occupies a central place in the entrepreneurial ecosystem (Adebambo and Yan, 2018), acting as a barometer of how markets and investors perceive a startup’s performance and prospects. Unlike binary indicators such as funding status or exit events, valuation is inherently continuous and it evolves across funding rounds, reflecting the complex interplay of internal capabilities, firm performance, and external market conditions (Berre and Le Pendeven, 2023). Valuation shapes how founders and investors negotiate ownership and control, allocate resources, and incentivize employees through equity (Ferreira and Pereira, 2021). It signals a startup’s credibility to customers, partners, and future investors, influencing its ability to scale and compete. Hence, evaluating a startup focusing on valuation provides a clear, quantifiable indicator of progress, guides strategic decisions, and signals value to all stakeholders involved.

For VC investors, valuation growth directly determines exit returns and fund performance, making it a critical metric for capital allocation decisions. Each upward shift in valuation signals increased investor confidence, improved resource access, and enhanced stakeholder credibility. For entrepreneurs, valuation determines funding terms, strengthens bargaining

power, affects ownership dilution, and opens growth opportunities. Growing valuations also create momentum that attracts talent, fosters partnerships, and opens access to new markets. Conversely, unrealistic or inflated valuations can create pressures and risks that jeopardize the long-term sustainability of a venture and even result in valuation bubbles (Gornall and Strebulaev, 2020).

Valuation is not just a final price tag. It results from how investors interpret available information at each stage of the startup's life. Hence, valuation is not just a static outcome but a dynamic process that evolves with each funding stage. As startups mature, the type of information investors rely on and the weight they place on different signals change (Dhochak et al., 2024). This creates an opportunity to understand valuation not merely as a financial outcome, but as a reflection of how internal and external stakeholders interpret evolving signals over time (Franke et al., 2006). Such a perspective is essential for capturing the layered realities of startup decision-making and investor behaviour, particularly in high-growth, high-uncertainty contexts like India.

By foregrounding valuation as a key outcome, this thesis moves beyond traditional dichotomies of success or failure and effectively traces the fluid, iterative journey that startups undergo as they strive to scale, survive, and create a lasting impact.

1.4 A Comprehensive Theoretical Lens: Extending the *Jockey-Horse* Model

Disagreements over valuation are among the most common reasons for failed negotiations between entrepreneurs and venture capital firms (Baeyens et al., 2006). This persistent tension highlights the need for a clearer understanding of how valuation outcomes are formed and negotiated. Over the past three decades, researchers have sought to demystify this process by

identifying and formalizing the key factors that shape startup valuation (Berre and Pendeven, 2023). Building on this body of work, this study adopts a broader perspective to explore how multiple forces interact to influence valuation decisions in high-growth, high-uncertainty environments. By doing so, it aims to offer a more integrated lens through which the dynamics of startup valuation can be understood.

To examine startup valuation in a more holistic way, this thesis draws on and extends the widely cited *jockey-horse* framework (Kaplan et al., 2009). This framework suggests that investors evaluate startups based on two core dimensions: the *jockey*, representing the founder or founding team, and the *horse*, representing the underlying business model and operational performance.

While the *jockey-horse* model offers a useful starting point, it faces two key limitations. First, its scope is narrow as it primarily focuses on the founder (*jockey*) and the venture itself (*horse*), overlooking other influential forces that significantly shape valuation outcomes. Startups do not operate in isolation; the broader industry environment, including profitability of the industry, ease of exit, and competitive intensity, directly shapes how both entrepreneurs and investors assess opportunities and risks (Patel et al., 2020). Moreover, in case of startups, valuation is an outcome of negotiation and alignment between the entrepreneur and the investors providing capital. The characteristics of the investor, such as their reputation, experience, network, and bargaining power, can substantially influence the valuation agreed upon in funding rounds (Bock and Schmidt, 2015; Cumming and Dai, 2011).

Second, the framework is mainly applied to early-stage contexts in the existing literature. However, as startups mature and move through successive funding rounds, the factors influencing valuation evolve and expand. Research has paid less attention to how these dynamics evolve as startups mature.

Addressing these limitations, this study builds on the discussion using a threefold approach. First, it extends the traditional *jockey-horse* framework by adding the *meadows* (the industry context) and *trainer* (the investor) to provide a more holistic perspective on the forces shaping startup valuation.

Second, it applies this expanded *jockey-horse-meadows-trainer* framework across the startup life cycle, from seed to later-stage funding rounds, to examine how these elements interact and evolve over time. By framing startup valuation as the outcome of dynamic, interdependent forces, this study offers a more realistic and integrated understanding of how value is perceived and assigned in high-growth ventures.

Finally, this study shifts the lens to the VC investor's side by examining the factors that influence how much venture capital funding a startup secures. While prior research often focuses on whether a startup attracts investment at all, this study goes further by unpacking how founders' characteristics, firm-level financials, investor behavior, and industry context jointly shape the scale of funding decisions. By doing so, it addresses a critical yet underexplored aspect of startup financing, not just the binary outcome of funding versus no funding, but the determinants of how much capital is deployed. This extension deepens the understanding of how VCs weigh multiple signals to calibrate their investment size, adding nuance to the conversation about valuation and resource allocation in entrepreneurial finance.

1.5 Beyond Valuation: Understanding VC Funding Commitments

Building on the discussion of valuation drivers, the focus now shifts from how startups are valued to how much capital they receive from VC investors. Startup valuation provides a critical signal of how markets and investors perceive a venture's growth potential, but funding decisions reflect the tangible commitment of capital that investors are willing to make. Startups

with similar valuations may secure very different levels of investment, depending on investor perceptions, risk appetite, strategic alignment, and broader market conditions. Examining VC funding alongside valuation helps unpack whether the factors that drive perceived firm value also translate into real capital commitments.

In dynamic, information-scarce markets, investor behavior and market signals play a crucial role in shaping funding outcomes. Founder characteristics, financial fundamentals, and contextual factors combine to influence how much financing is actually deployed. For instance, even with strong financial performance, the final funding amount can hinge on investor-specific considerations such as the entrepreneurs' prior experience, syndication strategies, or signals from influential co-investors. Unpacking the drivers of VC funding thus complements the valuation perspective by showing whether funding decisions mirror valuation signals or reveal additional layers of investor judgment and strategic intent.

1.6 Need for the study

The question of what drives startups to succeed or fail remains one of the most enduring and consequential topics in entrepreneurship research. This question is far more than an academic exercise, and it carries real implications for entrepreneurs, investors, policymakers, and the broader economy.

For individuals considering launching a business, understanding the conditions that enable success is critical for funding negotiations, strategic pivots, and day-to-day resource management. For investors, clear insight into these drivers enables better screening, due diligence, and portfolio strategies, helping allocate scarce capital more effectively. For governments and ecosystem builders, understanding how new ventures behave under varying market and institutional conditions is key to designing policies that enable innovation, foster job creation, and strengthen national competitiveness.

Despite growing global interest in startups, there remain significant gaps in how we measure and explain what underpins their long-term success. Existing studies often rely on binary indicators such as whether a startup secures funding, exits through acquisition or initial public offering (IPO), or simply survives. These milestones matter, but they tell only part of the story. They fail to capture the dynamic, unfolding journey of how startups build, signal, and negotiate their value over multiple funding rounds.

Valuation offers a more nuanced, continuous lens for understanding this journey. It is not merely a number on a term sheet. It signals investor confidence, the venture's growth promise, and the market's perception of risk and reward. However, valuation is not shaped in isolation; it reflects a complex interplay of factors that span founder characteristics, firm performance, investor behaviour, and industry conditions. Despite this, these elements are rarely studied together in an integrated way. In addition, much of the existing literature tends to treat valuation and funding as interchangeable, without explicitly examining whether the same factors that drive how startups are valued also determine how much capital they actually secure. By addressing this gap, this study clarifies whether the signals that shape perceived value also translate into concrete funding outcomes or if additional layers of investor judgment and market dynamics come into play.

This need is especially urgent for emerging markets, where institutional contexts, investor behaviours, and founder dynamics diverge sharply from those in developed economies (Ahlstrom and Bruton, 2006; Cumming et al., 2023; Groh and Wallmeroth, 2016). The institutional, cultural, and economic realities in countries like India differ significantly, potentially altering how signals are interpreted and how valuation and VC funding decisions are made.

Against this backdrop, this study seeks to bridge these gaps by offering a comprehensive, multi-level framework that extends the well-known *jockey-horse* model to include the *meadows*

(industry context) and the *trainer* (investor behaviour). By capturing the dynamic interactions among founder attributes, firm performance, industry conditions, and investor behavior, the study aims to provide a richer and more realistic understanding of what drives startup valuation. Beyond valuation, the study also asks whether these drivers similarly shape venture capital funding decisions by examining the *investment amount* as the dependent variable. This additional perspective highlights how VCs translate these signals (founder experience and financial indicators) into actual capital commitments.

In this context, the study asks three central questions:

1. Does firm performance outweigh founder attributes in driving valuation for later-stage startups, and how does their interaction change as the firm matures?
2. To what extent does industry attractiveness affect valuation, and is this relationship conditioned by the financial health of startup firms?
3. How does venture capitalist overconfidence influence startup valuations, and is this relationship moderated by investor syndication?
4. What are the factors that drive the VC funding amount?

By examining both valuation and the scale of VC investment, the study captures how founders, firms, investors, and industry context interact to signal potential value and influence real funding outcomes. This dual focus helps unpack whether the same factors that boost a startup's perceived worth also translate into larger investment cheques or whether different combinations of founder qualities, financial signals, and investor sentiment drive the amount invested. In doing so, the research offers practical insights for founders looking to understand what attracts bigger funding rounds and for VC investors aiming to refine their investment allocation strategies in dynamic, uncertain markets.

1.7 Research Objectives

This study explores the key determinants of startup valuation by examining the interplay between founder characteristics, firm performance, investor behaviour, and industry conditions. Specifically, this study investigates the following research objectives;

1. To identify the firm-level factors that drive startup valuation
 - a) Estimate startup success probability using the binomial options framework and analyze the influence of founder characteristics and financial indicators in driving this probability
 - b) Evaluate the interaction of founder characteristics and financial indicators across different stages of the startup lifecycle
2. To assess the role of industry environment in shaping startup valuation
 - a) Construct an index of industry attractiveness and examine its impact on startup valuation.
 - b) Analyze the moderating role of financial health in the relationship between industry attractiveness and startup valuation.
3. To assess the influence of VC investors' overconfidence on startup valuation
 - a) Construct an overconfidence index of VC investors and evaluate its effect on startup valuation
 - b) Examine the moderating effects of investor syndication on the relationship between VC overconfidence and startup valuation
4. To identify the firm-level and macroeconomic factors that drive the VC funding amount

1.8 Organisation of Thesis

Chapter 2 provides a comprehensive review of the existing literature on the drivers of startup valuation, establishing the theoretical and empirical foundations for the study.

Chapter 3 examines how founder characteristics and firm-level financial performance shape startup valuation, highlighting their relative importance across different stages of the venture's growth.

Chapter 4 analyses the role of industry attractiveness in determining startup valuation and tests whether the financial health conditions this relationship.

Chapter 5 investigates the influence of investor overconfidence on startup valuation and explores how investor syndication moderates this relationship.

Chapter 6 explores the founder characteristics, financial indicators, macroeconomic conditions, and deal features that influence the amount of venture capital funding.

Chapter 7 presents the overall discussion, key findings, contributions, concluding remarks, and directions for future research.

Chapter 2

Literature Review

In the dynamic landscape of modern business, startup enterprises stand out as driving forces of innovation and market growth. Understanding how these ventures are valued is vital, as valuation plays a central role in guiding investment decisions, resource allocation, and strategic planning. This chapter delves into the key drivers of startup valuation by drawing on both foundational and contemporary perspectives. This thesis begins with the foundational *jockey-horse* framework, emphasizing the interplay between founder characteristics (*jockey*) and firm performance (*horse*). This analogy is extended to incorporate industry conditions, akin to the “*meadows*” in which the firm operates, and investor characteristics, who are viewed as the “*trainer*” shaping the startup’s journey. This chapter examines how these factors interactively influence startup valuation through a comprehensive review of the literature. In addition, this chapter considers prior work on the determinants of venture capital funding to see how these shape funding levels.

The chapter is structured as follows:

Section 2.1 introduces the concept and significance of startup valuation

Section 2.2 outlines the major determinants of valuation

Section 2.3 discusses the *jockey-horse* framework

Section 2.4 reviews the role of industry conditions in driving startup valuation

Section 2.5 outlines the studies discussing the impact of investor behavior on startup valuation

Section 2.6 reviews the drivers of VC funding drivers

Section 2.7 lists the research gap that guides this study

Section 2.8 presents the conceptual framework

2.1 Startup valuation

An independent valuation of a startup firm is essential to reduce the potential conflict between the entrepreneur and investors as well as to design a structure that aligns the ambitions of both parties (Ferreira and Pereira, 2021). According to traditional corporate finance theory, valuation, in simple terms, is the determination of the present value of a firm's expected future cash flows. While this framework is widely accepted for mature firms with established financial histories, it proves inadequate for startups, which typically operate under conditions of limited historical data, significant uncertainty, and high growth potential (Damodaran, 2009). Despite its central importance, there is no globally agreed-upon valuation methodology for start-ups. This leaves business owners and investors with the challenging task of figuring out how to determine the value of a new venture. Hence, the most prevalent causes of failed talks between entrepreneurs and venture capital investors are differing viewpoints on valuation (Baeyens et al. 2006). Consequently, despite its pivotal role in shaping investment outcomes, startup valuation remains among the most contested and less standardized areas in entrepreneurial finance.

2.2 Determinants of startup valuation

Startup valuation lies at the core of entrepreneurial finance, yet practices surrounding it remain ambiguous due to the inherent complexity and diversity of startup ecosystems. This ambiguity has fueled growing academic and practical interest in identifying the key drivers of startup valuation. Scholars have explored a range of observable factors, both financial and non-financial, that may account for valuation differences across startup firms. The relative importance of these factors often varies with a startup's stage of development and the broader

industry context. The following section synthesizes insights from the existing literature on these determinants based on the stages of development of the startups.

A substantial body of work in startup valuation focuses on early-stage firms (Corea et al., 2021). In this context, investors often lack access to comprehensive financial records and instead base their valuation decisions on qualitative signals such as founder background, team composition, education, prior entrepreneurial experience, and social capital. This emphasis reflects the pivotal role of human capital in shaping expectations about a startup's future potential during its formative phase (Quas et al. (2021). Consequently, over the past two decades, research in entrepreneurial finance has primarily examined early-stage investment frameworks, where observable, non-financial traits drive valuation decisions. Among the most widely studied determinants are founder and team attributes, such as prior entrepreneurial experience, educational background, and team composition (Azoulay et al., 2020; Franke et al., 2006; Hsu, 2007; Müller and Murmann, 2016). Recent data-driven approaches have further formalized these insights by identifying structured checklists of key founder-related and team-related features that correlate with investor interest and funding outcomes (Corea et al., 2021). These findings reflect that, in the early stages of a startup's life cycle, human capital and leadership potential act as proxies for future firm performance in the absence of concrete financial data (Müller and Murmann, 2016).

As startups progress beyond their formative phases, the basis for valuation shifts markedly. While qualitative signals dominate valuation considerations in the early stages, the relative importance of financial indicators increases as startups mature. In later-stage ventures typically characterized by more structured operations and the availability of historical financial data, investors increasingly focus on quantitative assessments of firm performance (Hand, 2005).

This transition reflects the evolving expectations of investors, who increasingly prioritize demonstrable financial health and scalability when assessing mature startups. Metrics such as revenue growth, profitability, capital structure, and asset composition become more central to valuation decisions (Sievers et al., 2013), reflecting the transition from potential to performance-based evaluation. This shift underscores the evolving nature of investment criteria across a startup's lifecycle and highlights the need for a more integrated understanding of both financial and non-financial determinants of valuation. However, the financial factors contributing to the startup valuation are under-researched due to limited data availability.

Beyond firm-specific characteristics, broader-level factors at the ecosystem or institutional level can significantly shape startup valuation. These include the maturity of the entrepreneurial ecosystem, availability of supporting infrastructure, access to skilled labor, intellectual property protections, and government policies promoting innovation and funding (Cumming et al., 2017). Startups embedded in well-developed ecosystems such as Silicon Valley often benefit from positive externalities, including knowledge spillovers, network effects, and investor proximity, collectively contributing to higher valuations. Institutional support through accelerators, incubators, and startup-friendly regulations can further reduce perceived risks and enhance the appeal of ventures to potential investors (Lerner, 2010). Thus, valuation is not merely a function of internal capabilities or investor preferences, but also of the broader environment in which the startup operates. The contextual factors, such as industry dynamics and market conditions, also play a crucial role in shaping startup valuation. Industry attractiveness, competitive intensity, regulatory environment, and macroeconomic trends can influence both investor perceptions and the scalability potential of a venture (Patel et al., 2020). For instance, startups operating in high-growth or technology-driven sectors may command premium valuations due to heightened investor expectations about future returns.

In addition to firm and industry characteristics, the valuation of a young startup is often significantly influenced by the investors involved. Startup valuation is fundamentally the outcome of a negotiation between entrepreneurs and investors and is shaped by the expectations, preferences, and perceptions of both parties (Lukas et al., 2016). While founder attributes and firm-level characteristics are crucial, investor-related factors play an equally significant role in shaping valuation outcomes (González-Uribe, 2020). Prior research highlights that external signals associated with investors, such as the presence of syndicate partners, the size and reputation of the investment fund, geographic proximity to other funded ventures, and previous funding activity, can serve as powerful indicators of credibility and potential success (Cumming and Dai, 2011; Dai, 2010). These investor-related signals not only influence investor behavior but also reinforce the legitimacy of the startup in the eyes of the broader entrepreneurial ecosystem, thereby elevating its perceived valuation. Thus, valuation cannot be fully understood without accounting for the strategic and signaling roles that investors play in the startup financing process.

Taken together, these insights suggest that startup valuation is a multifaceted construct shaped by an interplay of internal capabilities and external signals, which vary meaningfully across development stages and industry contexts.

2.3 Founder characteristics and financial performance

Startup valuation is inherently complex, driven by uncertainty, limited historical data, and rapidly changing market conditions. The Resource-Based View (RBV) argues that a firm's sustainable advantage stems from its unique bundle of tangible resources and intangible capabilities (Barney, 1991). Applied through the *jockey-horse* framework, this perspective suggests that a startup's success hinges both on the quality of the *horse* or its financial and operational fundamentals, and the capability of the *jockey* or the founder who directs and leverages those resources effectively. In this context, the *jockey-horse* framework has emerged as a widely accepted lens for understanding how investors evaluate young firms. This framework emphasizes two critical components: the *jockey* representing the founding team's experience, vision, and execution capability; and the *horse* reflecting the underlying business model, market opportunity, and financial fundamentals.

The longstanding debate on how venture capitalists select startups - whether they bet on the founding team (*jockey*) or business performance (*horse*) remains unresolved. The proponents of the *jockey* perspective argue that an experienced, capable founder with strong leadership and strategic vision is essential for navigating early-stage uncertainties and securing investor confidence (Gompers et al., 2010). Conversely, the *horse* perspective emphasizes strong business potential and measurable performance indicators, such as revenue growth, profitability, and liquidity as key drivers of startup success (Hand, 2005).

Numerous studies have emphasised that early-stage firms are assessed primarily on the characteristics of their founders (*jockey*) (Ang et al., 2022). The founder's experience and team composition (Ang et al., 2022; Hsu, 2007; Pollock et al., 2010), are found to be crucial

for assessing the startup's capacity to execute its business plan and adapt to challenges. The prior entrepreneurial and managerial experience of the founding team is a primary non-financial valuation driver (Sievers et al., 2013). The founding team exemplifies the strategic vision of the firm and helps it navigate competitive markets. Experienced entrepreneurs possess stronger negotiation skills, enabling them to attract equity funding at increased valuations (Hsu, 2007). While these factors are well-documented for early-stage firms, it is unclear whether VC investors continue to prioritise *jockey* at later stages. This raises an important question: Does the significance of the founding team persist in influencing valuations as startups mature?

The existing literature on early-stage investments suggests that investors predominantly prioritise *jockey* (Esen et al., 2023). However, the importance of business-level attributes (*horse*) cannot be underestimated. As startups mature and seek to expand, they increasingly depend on VC funding to scale up operations, innovate, and remain competitive (Korosteleva and Mickiewicz, 2011). Funding at these stages involves considerable resource commitment (Worakantak et al., 2024). Hence, the financial performance reflecting the firm's profitability, liquidity, and growth becomes more relevant (Armstrong et al., 2006; Hand, 2005; Sievers et al., 2013). These performance indicators signal a firm's overall performance, enabling investors to gauge its potential for long-term sustainability. However, there is limited evidence on how this information influences the valuation of VC-backed startups, especially in contrast to publicly listed companies (Gavious and Schwartz, 2011). The limited available literature provides mixed evidence regarding the significance of cash and non-cash assets, long-term debt, revenue from operations, administration costs, and RandD expenditure (Hand, 2005; Sievers et al., 2013).

2.4 Industry attractiveness and startup valuation

“The myth is that venture capitalists invest in good people and good ideas. The reality is that they invest in good industries” (Zider, 1998). Given the scarcity of historical performance data and the high volume of startup applications, VCs commonly turn to industry-level signals as a practical means of screening and assessing potential investments (Que and Zhang, 2021).

The Market-Based View (MBV) emphasizes that firm performance is heavily shaped by the external environment and industry structure in which it operates (Porter, 1980). In the startup context, this perspective suggests that factors like industry attractiveness play a pivotal role in shaping funding and valuation outcomes by defining the competitive dynamics and growth potential accessible to founders and investors. Supporting this, prior research also acknowledges that industry-level factors, such as profitability, market liquidity, and exit opportunities, play a significant role in shaping VC investment decisions (Gompers et al., 2008). Industries with higher return on invested capital (ROIC), more active M&A markets, and greater IPO activity tend to attract higher investor interest.

However, within these attractive industries, not all startups perform equally; some consistently achieve higher valuations than others. This variation suggests that industry attractiveness alone may not fully account for valuation differences. It raises the question of whether such differences are driven by fundamental financial improvements at the firm level or by investor sentiment and attention. This tension brings two additional perspectives into focus. On one hand, the attention-driven view posits that startups in popular industries may receive more funding and higher valuations regardless of their intrinsic performance (Que and Zhang, 2021). On the other hand, the fundamentals hypothesis contends that valuation should primarily reflect firm-specific financial strength, including profitability, operational efficiency, liquidity, and

capital structure. This view suggests that investors ultimately reward sound financial health and growth potential, even in sectors subject to hype.

While industry attractiveness and attention given to such sectors can facilitate capital access and visibility for startups (Pan et al., 2020), it also introduces the risk of overvaluation if not grounded in firm fundamentals. Therefore, it becomes essential to examine how industry attractiveness interacts with firm-level fundamentals in shaping startup valuations. Doing so helps clarify whether high valuations stem from genuine financial performance or are merely amplified by prevailing industry sentiment.

2.5 Investor behaviour and startup valuation

Beyond firm performance, the valuation process is also shaped by the judgment and decision-making of the investors involved. VCs play a critical role in shaping the growth trajectories of new ventures and driving innovation within broader entrepreneurial ecosystems (Bonini and Capizzi, 2019). Given that VCs operate in a high-uncertainty environment where valuation is a result of negotiations between entrepreneurs and investors, the investor characteristics significantly influences investment decisions and post-money valuations.

According to the *Selection Hypothesis* (Brander et al., 2002), VCs generate superior returns primarily by identifying and selecting startups firms with growth potential. They are regarded as experts in identifying and funding high-growth startups (Zacharakis and Meyer, 2000). Their ability to assess risk, evaluate market potential, and provide strategic guidance makes them key players in the startup landscape (Bustamante et al., 2021). However, studies suggest that specialised knowledge in a field can make cognitive biases less noticeable and harder to overcome (Hoffrage, 2022). VCs, as highly specialised investors, are particularly susceptible

to this phenomenon. Their deep industry knowledge and experience may lead to overconfidence in their judgment, reinforcing biases in investment decisions.

In general, VCs are inherently optimistic, ambitious, and risk-taking investors. This confidence is essential for identifying high-potential startups, optimizing their portfolio investments, and guiding successful exits via mergers and acquisitions and public offers (Ben Amor and Kooli, 2024). However, excessive optimism overestimates a startup's probability of success, resulting in misjudged valuations and investment risks.

When it comes to the experts' arena, overconfidence has been analyzed in the mutual fund industry, where research shows that fund managers often overestimate their stock-picking abilities, leading to mispricing and suboptimal investment performance (Adebambo and Yan, 2018; Puetz and Ruenzi, 2011). However, VC literature has largely overlooked the role of overconfidence in startup valuation. While previous research examined factors like financial expertise, risk perception, and investment strategies (Cumming et al., 2005; Dai, 2010; Hsu, 2007), the direct impact of investor overconfidence on how VCs assess and price the startups remains underexplored.

One of the distinctive aspects of the VC industry is syndication (Brander et al., 2002; Tian, 2012). In syndicates, multiple investors invest in a single firm, and their diverse skills and information contribute to improved decision-making and advisory capabilities. Syndication enhances firm selection (Lerner, 1994), reduces individual capital exposure, and allows diversification of risks across multiple ventures (Lockett and Wright, 1999; Manigart et al., 2006). This collaborative approach also helps to minimize informational asymmetries by bringing multiple investors into the evaluation process. Each participating investor conducts independent due diligence, contributing diverse insights and cross-validating key assumptions about the startup's potential (Sorenson and Stuart, 2001) which minimizes the risks associated

with individual investor biases. Hence, syndication fosters more disciplined investment behavior.

2.6 Drivers of venture capital investment

While the broader venture capital literature has long emphasized why startups seek external finance, the specific determinants of VC investment size is underexplored. The funding amount received by a young firm determines its runway for growth, product development, market expansion, and talent acquisition (Gompers and Lerner, 2001).

Past research has mainly examined funding size indirectly, often linking it to factors like information asymmetry, signaling theory, or bargaining power (Admati and Pfleiderer, 1997; Cumming et al., 2005). For instance, syndication among multiple investors is shown to mitigate risks and increase the scale of funding rounds (Hochberg et al., 2007). Similarly, founder reputation, prior successes, or prestigious educational backgrounds can reassure investors and influence the size of their financial commitment (Hsu, 2007). Operational track record and credible financials further strengthen the negotiation position for higher funding (Howell, 2020).

However, the funding amount is not merely the result of static firm attributes. It reflects dynamic investor expectations, risk perceptions, and changing market conditions (Ang et al., 2022; Jeng and Wells, 2000; Lukas et al., 2016). External factors and behavioral biases can amplify or dampen the capital flow to startups (Nanda et al., 2020). Examining funding amounts alongside valuation enriches the understanding of how signals and context are translated into actual capital deployed. This perspective helps move beyond abstract firm worth to reveal how investors back their beliefs with real resources. As funding amounts directly influence startups' survival chances and scaling capacity (Stevenson et al. 2019), analyzing

their determinants adds an essential dimension to the discourse on entrepreneurial finance. This would align with the practical narrative and recognizes capital as both a vote of confidence and a binding constraint for growth.

2.7 Research gaps

The valuation of startups is a complex process influenced by multiple factors. Despite the growing attention to startup funding and valuation, several important gaps persist in the literature. First, much of the existing research has traditionally framed entrepreneurial success in binary terms (funded versus unfunded, exit versus no exit), overlooking the nuanced, continuous nature of startup valuation as a forward-looking indicator of success. While recent studies have begun to incorporate valuation into models of startup performance, they often focus on static snapshots rather than how valuations evolve across funding rounds and stages.

Second, while the Resource-Based View (RBV) (Barney, 1991) and the classic *jockey–horse* framework have highlighted the critical roles of founder characteristics and firm financial quality in shaping startup outcomes, the financial component remains underexplored in empirical detail. Few studies systematically unpack which specific financial indicators matter most for scaling valuations in risky, high-growth contexts and how their influence may shift as startups mature.

Third, although industry-level factors are widely acknowledged to shape venture capital decisions (Sahaym et al., 2010), much of this work focuses on investment volumes or sector-level trends rather than firm-level valuation. The role of industry attractiveness in scaling valuation outcomes remains under-investigated.

Fourth, existing studies seldom account for investor behavior, such as overconfidence, and its interplay with firm and industry signals in shaping funding decisions. This is especially

relevant in emerging markets, where information asymmetries and hype cycles can amplify valuation volatility.

Finally, the geographical scope of empirical research in entrepreneurial finance remains skewed toward developed economies. The United States and European nations dominate the field, largely due to data accessibility and mature startup ecosystems (Oino, 2014). However, emerging economies such as India present a fundamentally different entrepreneurial landscape. It is also documented that findings from developed contexts may not be directly generalizable to emerging markets (Bustamante et al., 2021). Despite India's rapid rise as a global startup hub, empirical studies using robust financial data remain scarce, with much of the existing work relying on qualitative methods (Kalyanasundaram et al., 2021).

Addressing these gaps, this thesis integrates multiple perspectives - founder capabilities, financial fundamentals, industry context, and investor behavior to offer a more holistic and dynamic understanding of what drives startup valuation and VC funding amounts across stages.

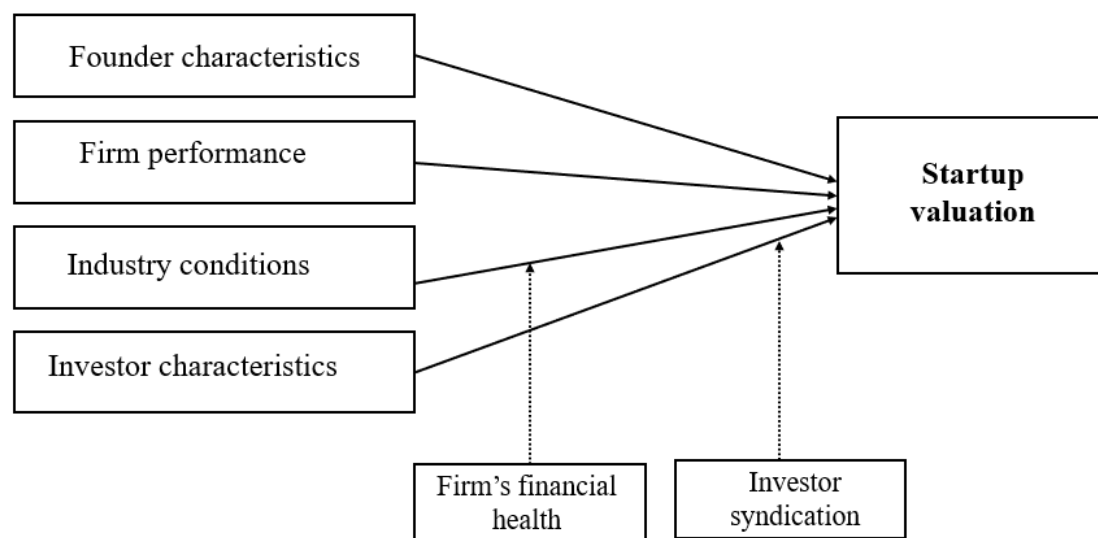
2.8 Conceptual framework

Building on the various theoretical and empirical insights discussed above, this thesis integrates these determinants into a unified framework to better understand how startup valuation is shaped. Specifically, this study considers the combined influence of firm-level founder and financial metrics, investor behavior, and industry-level attractiveness on startup valuation outcomes. However, these drivers do not operate in silos. Their effects may be shaped by contextual factors. Specifically, syndication may enhance the objectivity and quality of investor decision-making, while strong financial fundamentals can amplify or temper the valuation effects of industry and investor-related variables. This approach enables us to examine both fundamental and contextual drivers in a cohesive manner. The conceptual model

that follows illustrates the hypothesized relationships among these key variables and guides the empirical investigation. The conceptual model is depicted in Figure 2.1.

Figure 2.1 Conceptual model

This figure illustrates the conceptual framework for the study, showing how founder characteristics, firm performance, industry conditions, and investor characteristics influence startup valuation. The model also depicts the moderating roles of the firm's financial health and investor syndication on these relationships.



Chapter 3

Interplay of founders and financials in predicting startup valuation

3.1 Research context

An increase in startup valuation directly translates into higher exit returns for venture capital (VC) investors (Lerner and Nanda, 2020) and serves as a dynamic and forward-looking indicator of a startup's success. However, the traditional research often simplifies entrepreneurial success into binaries - funded versus unfunded or exit versus no exit (Bock and Schmidt, 2015; Cumming et al., 2017; Guo et al., 2015; Nanda et al., 2020). While such milestones are important, they miss the fluid, dynamic journey of a startup. This study rewrites the success narrative and argues that valuation serves as a more granular and continuous indicator of a startup's trajectory. Accordingly, the probability of a startup achieving higher valuations in the subsequent funding round is estimated using the binomial options framework (Reber, 2014) and the key factors shaping this success probability are then examined.

Resource-Based View (Barney, 1991) highlights that internal resources, such as founder capabilities and financial quality, significantly influence a firm's growth and performance. While founder capabilities indicate the intangible human capital (Azoulay et al., 2020; Esen et al., 2023; Murmann et al., 2020), the financial performance reflects on the tangible operational efficiency of a venture (Armstrong et al., 2006; Hand, 2005; Sievers et al., 2013). These are observable signals prior to investment and thus play a key role in shaping investor expectations and strategic decisions (Miloud et al., 2012).

Grounded in the classic *jockey-horse* framework and Resource Based View, this study explores how the qualities of the *jockey* (the founder) and the *horse* (the firm's financial fundamentals) work in tandem to influence startup valuation. Drawing on a sample of 1,100

VC-backed funding rounds in India, the study uses beta regression and SHapley Additive exPlanations (SHAP) to unpack the key founder and financial factors that drive the probability of startup success.

While this study adopts the *jockey–horse* metaphor to conceptually frame startups as a combination of founder quality (*jockey*) and firm fundamentals (*horse*), the results and discussion sections refer to these dimensions more directly as founder characteristics and financial indicators. This practical phrasing maintains clarity, avoids unnecessary repetition of the metaphor, and aligns with how these variables are operationalised and measured in the empirical models.

The rest of the chapter is organized as follows: Section 2 outlines the research methodology and describes the data sample. Section 3 discusses the results and findings. Section 4 concludes with key takeaways from the study.

3.2 Data and Methodology

3.2.1 Sample description

India is home to over 157,000 startups and is one of the world's largest and fastest-growing entrepreneurial ecosystems (Ministry of Commerce and Industry, 2025). Yet, fewer than 10% of these ventures survive beyond the first five years (IBM, 2017). A key challenge for entrepreneurs and VC investors operating in such a dynamic environment is identifying the factors that enable startups to scale and succeed. Against this backdrop, the Indian startup ecosystem provides a compelling setting to explore how young firms navigate the path to sustained success.

This study uses data from Tracxn on Indian startups that received VC funding between January 1, 2011, and December 31, 2021. The sample includes firms with at least two consecutive rounds of post-money valuations available. After excluding firms with missing valuation,

founder, or financial data, the final dataset comprises 1,100 funding rounds. The sample summary is provided in Table 3.1.

Table 3.1 Sample distribution

This table presents the distribution of the sample across industries (Panel A) and funding rounds (Panel B). Panel A reports the number of unique startups in each industry category (N = 530), while Panel B shows the number of venture capital funding rounds observed across different stages (N = 1,100).

Panel A: Industry-wise sample distribution	
Industry	Number of startups
Fin tech and Services	100
Retail	88
IT and Services	56
Health Tech and Services	53
Ed Tech	29
Others	204
Total	530
Panel B: Round-wise sample distribution	
Round	Number of rounds
Seed	319
Series A	360
Series B	194
Series C+	227
Total	1100

3.2.2 *Variable measurement*

3.2.2.1 *Estimation of success probability*

A substantial body of literature has examined the determinants of startup success, often defining success through binary outcomes such as securing follow-on funding (Bock and Schmidt, 2015; Cumming and Johan, 2009) or achieving an exit via acquisition or initial public offering (Gompers et al., 2010; Nguyen and Vo, 2021). While these milestones are important, they may overlook the continuous nature of a startup's growth.

Valuation is a more nuanced indicator that drives the narrative around a startup's growth and potential (Cumming and Dai, 2011). However, because private firm valuations are infrequently and irregularly disclosed, modeling their growth with continuous-time methods is challenging. Hence, most empirical studies have not incorporated valuation into outcome assessments. To navigate this limitation, researchers have increasingly adopted alternative frameworks that use the real options option framework (Hsu, 2010; Lukas et al., 2016; Tennert et al., 2018; Trabelsi and Siyahhan, 2021). This approach makes it possible to track startup growth through valuation and express it as a continuous measure of success (Reber, 2014). It also captures the incremental nature of venture growth and aligns with how VC investors assess future potential.

The Cox–Ross–Rubinstein (CRR) binomial option pricing framework (Cox et al., 1979) offers a practical solution that treats each funding round as a separate step. Following Reber (2014), this study apply the CRR model to estimate the risk-neutral probability of success, using the post-money valuation as input. This probability, which falls between 0 and 1, represents the likelihood of the startup reaching higher valuations in future rounds, adjusted for the risk-free rate.

The following equation gives the estimation:

At the start of period t , the firm's value for stage s , denoted $V_{t,s}$, may either increase to V^u or decrease to V^d over one period (t, T) . The up movement in firm value u_s is

$$u_s = \frac{V_{T,s}^u}{V_{T,s}^d}, \text{ such that } u_s > 1 \text{ and} \quad (1.1)$$

$$d_s = \frac{1}{u_s}, \text{ such that } 0 < d_s < 1 \quad (1.2)$$

u and d allow calculating the implied risk-neutral success probability of an up-movement p for each stage s as follows:

$$p_s = \frac{e^{r_{f,s}(T-t)s} - d_s}{u_s - d_s}, 0 \leq p_s \leq 1 \quad (1.3)$$

Using the CRR framework allows us to view a startup not just as a firm, but as a growth option, an approach that closely mirrors how VCs assess a startup's potential. Rather than relying solely on static valuations or binary outcomes like success vs. failure, the CRR model captures the dynamic, staged nature of startup growth, accounting for both upside potential and embedded uncertainty (Thoma, 2023). This makes it a more nuanced and realistic tool for evaluating startup success.

3.2.2.2 Independent Variables

To investigate the drivers of startup valuation and VC funding, this study includes a comprehensive set of independent variables capturing both founder-specific characteristics and firm-level financial indicators. Drawing from the classic *jockey-horse* lens, the founder attributes (*jockey*) are operationalized through measures such as entrepreneurial experience (proxied by the logged count of prior startups), managerial experience, premier institute

education, geographic location in a recognized startup hub, and gender diversity among founders. These variables reflect the human and social capital signals that are often used by investors to gauge founder competence, credibility, and network advantages.

In parallel, the firm's financial fundamentals (*horse*) are examined through liquidity, solvency, and operational efficiency ratios that signal financial health and scalability potential. Liquidity and solvency are represented by cash-to-current liabilities, cash-to-total assets, and debt-to-equity ratios, while operational efficiency is captured through fixed asset turnover, operating expense to revenue ratio, and revenue-to-cash ratio. These metrics provide granular insights into how well a startup manages its resources and generates revenue relative to its asset base and cash reserves.

3.2.2.3 Control variables

Firm age is included as a key control variable, as startups with a longer operational track record often have more stable performance histories, greater visibility, and stronger reputations, all of which can positively influence valuation outcomes (Cumming and Dai, 2011). Deal-level characteristics, such as investor syndication, and presence of institutional investors, also play a critical role in shaping funding and valuation outcomes (Berre and Le Pendeven, 2023). Investor syndication, or the collaboration of multiple investors, adds credibility to a startup, enhancing its value by pooling expertise, resources, and networks (Manigart et al., 2006; Tian, 2012). Similarly, the involvement of institutional investors is often seen as a vote of confidence, as these investors typically conduct thorough due diligence, thereby boosting both the startup's perceived legitimacy and its valuation (Bustamante et al., 2021). Table 3.2 provides detailed descriptions of all variables used in the analysis.

Table 3.2 Variable description of founder and financial indicators

This table provides definitions for all variables used in the analysis.

Variable	Description
<i>Dependent variable:</i>	
p	Risk-neutral success probability estimated using CRR model, refer Eq.3
<i>Founder characteristics:</i>	
<i>Entrepreneurial experience</i>	Natural log of the number of prior startups founded by the founder, plus one
<i>Managerial Experience</i>	Binary variable, '1' if the founder has prior managerial experience, '0' otherwise
<i>Premier institute education</i>	Binary variable, '1' if founder had premier educational institution ^a , '0' otherwise
<i>Geographic location</i>	Binary variable, '1' if the firm is in a recognized startup hub ^b , '0' otherwise
<i>Female founders</i>	Natural log of the number of female co-founders in the team, plus one
<i>Financial indicators:</i>	
<i>a) Liquidity and solvency indicators</i>	
<i>Cash/Current liabilities</i>	Total cash and bank balance divided by current liabilities
<i>Cash/Total Assets</i>	Total cash and bank balance divided by total assets
<i>Debt/Equity</i>	Total debt divided by shareholders' equity
<i>b) Operational efficiency indicators</i>	
<i>Fixed asset turnover</i>	Total revenue from operations divided by fixed assets
<i>Operating expense/Revenue</i>	Total operating expenses divided by total revenue from operations
<i>Revenue/Cash</i>	Total revenue from operations divided by cash and bank balance
<i>Controls:</i>	
<i>Firm age</i>	Natural log of funding year minus startup founded year, plus one
<i>Investor syndication</i>	Natural log of total number of investors in the current funding round, plus one
<i>Institutional investor</i>	Binary variable, '1' if institutional investors participated in previous funding round, '0' otherwise

Note: a) For the purpose of this study, premier educational institutions are defined as IITs, IIMs, IISc, IISERs, and AIIMS

b) Recognized hubs are defined as the top four startup locations in India- Bengaluru, Mumbai, Delhi, and Hyderabad

3.2.3 Analytical framework

3.2.3.1 Heckman Sample Selection

Since the analysis is limited to startups with publicly available financial information. This restriction introduces the potential for sample selection bias. To correct for this, the study implements the Heckman sample selection model (Heckman,1979). In the first stage, a probit model to capture the likelihood of a startup disclosing financial data is considered.

The Heckman equation is:

$$\begin{aligned} \text{Likelihood of financials available} = & a_0 + a_1 \text{number of funding rounds} + \\ & a_2 \text{investor syndication} + a_3 \text{GDP growth rate}_{t-1} + \varepsilon \end{aligned} \quad (1.4)$$

From this model, the inverse Mills ratio (*imr*) is derived, which is then included in the second-stage beta regression. This ensures that the estimation of startup success drivers is not biased due to non-random sample inclusion.

The number of funding rounds is the natural log of funding rounds before the current investment, and the number of investors indicates the natural log of the total number of investors in a given round. The GDP growth rate of the previous year is also considered in the selection equation.

The instruments are selected based on theoretical relevance and data availability. The number of funding rounds reflects the startup's historical success in attracting funding, signalling its credibility and growth potential to investors (Barg et al., 2021). Similarly, the number of investors in a given round serves as a proxy for investor confidence and syndication strength (Bayar et al., 2020; Tian, 2012). Additionally, the GDP growth rate of the previous year

represents macroeconomic conditions that influence the investment activity and business success of startup firms (Ning et al., 2015, 2019).

3.2.3.2 Beta regression

The dependent variable in this study is the risk-neutral success probability of startups, denoted by p , which takes values between 0 and 1. Given the bounded and continuous nature of this variable, the study employs beta regression as the appropriate methodological framework. It accommodates heteroskedasticity and skewness by assuming a beta distribution and relies on maximum likelihood estimation to provide efficient and interpretable parameter estimates (Cribari-Neto and Zeileis, 2010; Ferrari and Cribari-Neto, 2004).

The beta regression equation is as follows;

$$p_{j,s} = \alpha + \beta(\text{founder characteristics})_j + \delta(\text{financial indicators})_s + \gamma(\text{controls})_s + imr + \epsilon_{j,s} \quad (1.5)$$

In this specification, $p_{j,s}$ represents the probability of success for startup j in funding round s . The model estimates how founder characteristics, firm-level financial indicators, and relevant control variables jointly influence this probability. The variable description of all the independent variables is provided in Table 3.2. The model also includes an inverse Mills ratio (imr), as indicated in Equation (1.4), to correct for potential selection bias. $\epsilon_{j,s}$ is the error term capturing unobserved influences on the outcome.

3.2.3.3 SHapley Additive exPlanations (SHAP)

To gain a more granular understanding of how various firm-level factors influence success probability, the study employ SHapley Additive exPlanations (SHAP). SHAP is a model-agnostic framework rooted in cooperative game theory (Li and Wu, 2024). It quantifies the marginal contribution of each variable to the model's output (Siddique and Karim, 2025). It helps to uncover complex patterns, highlight variable interactions, and provide visual insights into how founder attributes and financial indicators shape startup outcomes (Garitta and Grassi, 2025). In this study, the SHAP values are derived from an XGBoost model, which is selected for its high predictive accuracy and ability to model complex, non-linear relationships.

3.3 Empirical results

3.3.1 Descriptive statistics

Table 3.3 presents the descriptive statistics for the variables used in the analysis. The startup success probability has a mean of 0.370 and median of 0.353, highlighting both the growth potential and the inherent uncertainty faced by early-stage ventures.

Among founder characteristics, prior entrepreneurial experience is relatively low on average (mean = 0.25), indicating that many founders are first-time entrepreneurs. Managerial experience, on the other hand, has higher average (mean = 0.79), indicating that a large proportion of founders have held managerial roles before starting up. Similarly, about half of the sample comes from premier educational institutions and a majority of startups are located in recognized startup hubs.

Table 3.3 Descriptive statistics of founder and financial indicators

This table reports descriptive statistics for the variables used in the analysis, including the mean, standard deviation, and median. Please refer Table 3.2 for variable definitions. The nature of the variable is mentioned in the brackets.

Variables	count	mean	std	median
<i>p</i>	1100	0.370	0.214	0.353
<i>Entrepreneurial experience(ln)</i>	1100	0.253	0.423	0.100
<i>Managerial experience(binary)</i>	1100	0.787	0.112	1.000
<i>Premier institute education (binary)</i>	1100	0.505	0.500	1.000
<i>Female founders (ln)</i>	1100	0.209	0.356	0.000
<i>Geographic location (binary)</i>	1100	0.657	0.475	1.000
<i>Cash/Current liabilities (ratio)</i>	1100	0.432	0.507	0.308
<i>Cash/Total assets (ratio)</i>	1100	0.629	0.277	0.572
<i>Debt/Equity (ratio)</i>	1100	2.507	3.546	0.510
<i>Fixed asset turnover (ratio)</i>	1100	7.585	8.548	4.065
<i>Operating expense/Revenue (ratio)</i>	1100	2.994	2.620	1.683
<i>Revenue/Cash (ratio)</i>	1100	4.042	3.737	3.419
<i>Firm age (ln)</i>	1100	1.549	0.703	1.609
<i>Investor syndication (ln)</i>	1100	1.558	0.814	1.386
<i>Institutional investor (binary)</i>	1100	0.946	0.225	1.000

In terms of financial indicators, the average cash-to-current liabilities ratio is 0.43, and the mean cash-to-total-assets ratio is 0.63, indicating moderate liquidity across firms. The average debt-to-equity ratio is relatively high at 2.51, but with substantial variation, highlighting differences in capital structure choices. Operational efficiency metrics reveal a mean fixed asset turnover of 7.59, an operating expense-to-revenue ratio of 2.99, and a revenue-to-cash ratio of 4.04, suggesting diverse approaches to asset utilization and cost management.

Among the control variables, the mean firm age (natural log) is about 1.55, indicating that the firms in the sample are relatively young. The average age of sample firms is 5 years in absolute firms. Investor syndication also shows that many startups enjoy syndicated deals involving multiple investors. Notably, institutional investor involvement is high, reflecting that most funding rounds include institutional investors, which can further influence valuation outcomes.

3.3.2 *Founder characteristics and startup success probability*

While much of the entrepreneurship literature acknowledges the pivotal role of founders in shaping venture outcomes (Hsu, 2007), evidence on which specific founder characteristics drive success remains mixed (Müller and Murmann, 2016). This section fills that gap by empirically testing the relationship between founder characteristics and startup success probability. The founders' prior entrepreneurial and managerial experience is a key driver VCs use in early-stage screening (Corea et al., 2021; Zott and Huy, 2007).

Beta regression results in Table 3.4 indicate that founder characteristics, particularly managerial experience and entrepreneurial experience, show a significant positive relationship across Models (1) to (5). This is consistent with the findings of existing literature (Hsu, 2007; Zott and Huy, 2007). Other founder attributes, such as premier education, gender, and geographic location, do not exhibit significant effects.

The consistent significance of firm age suggests that the startup's survival in the ecosystem is itself a signal of viability. The inclusion of an inverse Mills ratio (*imr*) in Models (4) and (5) corrects for potential selection bias. In the Heckman two-stage model, the *imr* coefficient captures the direction and significance of selection bias. A positive and significant *imr* coefficient suggests positive selection, indicating that startups that are more likely to disclose financial data also tend to perform better due to greater transparency, credibility, or investor confidence.

Table 3.4 Founder characteristics and success probability

This table reports beta regression results estimating the impact of founder characteristics on success probability. See Table 3.2 for variable definitions. Managerial experience, Premier institute education, Geographic location, and Institutional investor are binary variables. Industry, Year and Round level fixed effects are considered. Models (4) and (5) include the inverse Mills ratio (imr) to correct for potential selection bias. Robust standard errors are reported in parentheses. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively.

VARIABLES	(1) <i>p</i>	(2) <i>p</i>	(3) <i>p</i>	(4) <i>p</i>	(5) <i>p</i>
<i>Entrepreneurial experience</i>	0.107* (0.061)	0.115* (0.062)	0.096 (0.063)	0.105* (0.062)	0.112* (0.061)
<i>Managerial experience</i>	0.503** (0.242)	0.560** (0.246)	0.670*** (0.254)	0.593** (0.250)	0.441* (0.240)
<i>Premier institute education</i>	-0.050 (0.054)	-0.016 (0.053)	-0.009 (0.055)	-0.038 (0.054)	-0.069 (0.053)
<i>Female founders</i>	-0.011 (0.074)	-0.003 (0.074)	-0.056 (0.078)	-0.057 (0.077)	-0.023 (0.073)
<i>Geographic location</i>	-0.012 (0.055)	-0.015 (0.055)	-0.067 (0.057)	-0.075 (0.056)	-0.030 (0.054)
<i>Firm age</i>	0.323*** (0.045)	0.401*** (0.040)	0.401*** (0.042)	0.319*** (0.043)	0.278*** (0.046)
<i>Investor syndication</i>	-0.010 (0.034)	-0.006 (0.034)	-0.004 (0.035)	-0.108*** (0.038)	-0.101*** (0.039)
<i>Institutional investor</i>	0.168 (0.118)	0.148 (0.119)	0.134 (0.121)	0.124 (0.118)	0.150 (0.116)
<i>imr</i>				1.699*** (0.260)	1.558*** (0.267)
Constant	-1.522*** (0.276)	-1.678*** (0.583)	-1.494** (0.610)	0.777 (0.477)	0.542 (0.448)
Industry FE	No	No	Yes	Yes	No
Year FE	No	Yes	Yes	No	No
Round FE	Yes	No	No	No	Yes
Observations	1100	1100	1100	1100	1100
AIC	-534.198	-518.178	-506.165	-551.637	-586.141
BIC	-464.156	-418.117	-261.015	-351.514	-493.095
Log likelihood	281.100	279.089	302.083	315.818	352.736
LR chi2	149.83	145.81	191.79	219.27	185.77
Prob > chi2	0.000	0.000	0.000	0.000	0.000

To account for unobserved heterogeneity that could bias the estimated relationships, the models incorporate various fixed effects (FE) specifications. Specifically, industry fixed effects control for sector-specific dynamics and structural differences that may systematically influence startup valuation and funding decisions. Year fixed effects address time-specific shocks and macroeconomic conditions that could affect the funding environment or investor sentiment across periods. Additionally, round fixed effects capture systematic differences across funding stages, recognizing that early-stage and late-stage rounds may follow distinct evaluation criteria. By including these controls where relevant, the analysis ensures that the estimated effects of founder characteristics are not confounded by unobserved industry, temporal, or funding-round factors.

To evaluate the model's fit and parsimony, standard model diagnostics such as the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are reported. Lower values of AIC and BIC indicate a better-fitting model while penalizing for excessive complexity. The log likelihood reflects how well the model explains the observed data; higher values suggest a better fit. The likelihood ratio chi-squared (LR χ^2) statistic tests whether the full model provides a significantly better fit than a null model with no predictors. A significant LR χ^2 (with a small Prob > χ^2) indicates that the included independent variables, jointly, add explanatory power. Together, these statistics confirm that the model specification is appropriate and that the chosen predictors meaningfully explain variation in the probability of achieving higher valuations.

3.3.3 Financial indicators and startup success probability

As startups mature and seek to expand, they increasingly depend on VC funding to scale up operations, innovate, and remain competitive (Korosteleva and Mickiewicz, 2011). Funding at these stages involves considerable resource commitment (Worakantak et al., 2024). Hence, the

financial metrics reflecting the firm's profitability, liquidity, and growth become more relevant (Armstrong et al., 2006; Hand, 2005; Sievers et al., 2013). However, only a few studies have systematically examined the role of such financial metrics in startup contexts (Kaplan and Lerner, 2016). This limited empirical investigation is largely due to the challenges of accessing detailed financial data on privately held firms. This study addresses the research gap and contributes to the entrepreneurial literature by identifying the financial indicators that significantly drive success probability.

The study particularly focuses on financial ratios, as they standardize for firm size and scale differences, enabling meaningful comparisons across startups at varying stages of growth. Moreover, these ratios are widely used in entrepreneurial finance research to capture liquidity, leverage, and efficiency. Profitability ratios like earnings before interest and taxes (EBIT) margin were tested but dropped, as most startups had negative EBIT, and the variable was insignificant in regressions. Instead, the study focuses on operating efficiency, which offers more meaningful insights for younger firms. Financial ratios are calculated for the fiscal year preceding the funding year to account for potential lagged effects on valuation. This ensures that only information available prior to the valuation is used in the analysis.

Table 3.5 shows that financial indicators serve as critical signals of success potential, controlling for founder and firm-level characteristics. Models (1) to (4) sequentially introduce different financial ratios alongside founder and firm-level controls. Across specifications, the debt-to-equity ratio exhibits a consistently positive and statistically significant association with success probability, suggesting that higher leverage, when used strategically, is considered a signal of growth potential. This result is inconsistent with the findings of (Cole and Sokolyk, 2018; de Rassenfosse and Fischer, 2016).

Table 3.5. Financial indicators and success probability

This table reports beta regression results estimating the impact of financial indicators on success probability. See Table 3.2 for variable definitions. Financial ratios are calculated for the fiscal year preceding the funding year to account for potential lagged effects on valuation. Managerial experience and Entrepreneurial experience are also included, as they were significant in the previous model. Industry, Year and Round level fixed effects are considered. All the models include the inverse Mills ratio (*imr*) to correct for potential selection bias. Robust standard errors are reported in parentheses. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively

VARIABLES	(1) <i>P</i>	(2) <i>p</i>	(3) <i>p</i>	(4) <i>p</i>
<i>Cash/Current Liabilities</i>			0.114 (0.054)	0.110 (0.055)
<i>Cash/Total Assets</i>	0.198** (0.084)			
<i>Debt/Equity</i>		0.017** (0.007)		0.014* (0.007)
<i>Fixed Asset Turnover</i>		0.001 (0.001)	0.001 (0.001)	
<i>Operating Expense Ratio</i>	-0.018* (0.011)			-0.018* (0.011)
<i>Revenue/Cash</i>		0.002* (0.001)		
<i>Entrepreneurial experience</i>	0.114* (0.060)	0.121** (0.061)	0.122** (0.061)	0.101* (0.060)
<i>Managerial experience</i>	0.411* (0.238)	0.416* (0.239)	0.437* (0.240)	0.334 (0.236)
<i>Firm age</i>	0.256*** (0.048)	0.280*** (0.046)	0.277*** (0.046)	0.147*** (0.050)
<i>Investor syndication</i>	-0.095** (0.039)	-0.101*** (0.039)	-0.101*** (0.039)	-0.270*** (0.047)
<i>Institutional investor</i>	0.143 (0.117)	0.154 (0.116)	0.146 (0.116)	0.191 (0.115)
<i>imr</i>	1.562*** (0.265)	1.542*** (0.265)	1.492*** (0.267)	3.475*** (0.399)
Constant	0.590 (0.449)	0.428 (0.445)	0.423 (0.447)	2.698*** (0.754)
Industry FE	No	No	No	Yes
Year FE	No	No	No	Yes
Round FE	Yes	Yes	Yes	No
Observations	1100	1100	1100	1100
AIC	-574.498	-574.072	-573.087	-616.660
BIC	-504.455	-504.029	-503.044	-496.586
Log likelihood	301.249	301.036	300.543	332.330
LR chi2	190.13	189.70	188.72	252.29
Prob > chi2	0.000	0.000	0.000	0.000

Conversely, the operating expense ratio is negatively associated with success, reinforcing the role of cost efficiency in shaping valuation outcomes. Interestingly, entrepreneurial and managerial experience remain positive and significant, underscoring that the founders' experience matters. These findings are consistent across models and align with the broader interpretation that financial discipline overrides human capital in driving startup success.

The positive association between leverage and valuation growth needs to be interpreted within the institutional realities of startup financing. In contrast to public firms, where higher leverage is commonly associated with greater financial risk, debt in private startups plays a different role. Startup leverage frequently consists of instruments such as convertible notes, bridge financing, founder loans, or inter-corporate borrowings, which are typically provided by experienced investors with strong screening and monitoring capabilities. Access to such financing is therefore conditional on a startup's perceived quality and growth potential. In this setting, a higher Debt-to-Equity ratio is less indicative of aggressive risk-taking and more reflective of access to sophisticated and structured capital, aligning the empirical finding with the institutional context discussed earlier in the thesis.

Similarly, it is important to note that Fixed Asset Turnover ratio is used here as a context-specific indicator of operational efficiency rather than a comprehensive measure of startup performance. This limitation is particularly relevant for early-stage and digital-native firms, whose asset-light structures may weaken the interpretability of traditional asset-based efficiency ratios. However, this indicator is included to capture heterogeneity in asset-light versus asset-intensive business models, particularly across sectors such as manufacturing, health technology, and infrastructure-oriented startups in the sample.

Among the control variables, investor syndication has a significant negative influence. VCs tend to invest in groups, leading to smaller ownership stakes for each investor in larger

consortia. Smaller stakes reduce VCs' incentives to monitor and support the startup actively, and hence, a higher number of investors in a financing round is negatively correlated with valuation outcomes. This is consistent with the findings of Barg et al. (2021).

To address potential endogeneity concerns and strengthen the robustness of the findings, this study adopts a multi-faceted approach. First, the Heckman two-stage sample selection model corrects for possible selection bias arising from the non-random likelihood of startups disclosing or achieving valuations, ensuring that the estimates are not biased by sample truncation. The results indicate that the inverse Mills ratio (*imr*) remains significant, confirming the presence of sample selection bias and justifying its inclusion. Second, the inclusion of fixed effects such as industry, year, and funding round controls for unobserved heterogeneity that may otherwise confound the relationship between founder or financial factors and valuation outcomes. Third, lagged independent variables are used where applicable to help mitigate reverse causality by ensuring that current funding decisions are explained by prior-period firm characteristics rather than simultaneous effects. Together, these steps enhance the credibility of the findings and provide a more rigorous empirical foundation for interpreting how observable startup signals shape valuation and funding outcomes. Overall, the model diagnostics (AIC, BIC, log likelihood, and LR χ^2) further support the robustness of the specifications, with consistently significant fit statistics across all versions.

3.3.4 SHAP-based variable importance

While the beta regression identifies the statistical significance and direction of effects, it does not reveal how different variables compare in their relative contribution to valuation outcomes for each observation. Incorporating SHAP-based variable importance provides an additional layer of insight by quantifying which founder and financial factors have the greatest practical

influence on predicted valuations. This allows for a more nuanced understanding of which signals matter most and complements the regression results with an interpretable, model-agnostic perspective.

In this study, the SHAP-based interpretation is grounded in an XGBoost model, which serves as the predictive engine for estimating startup funding amounts. XGBoost (Extreme Gradient Boosting) is a robust tree-based ensemble learning technique that efficiently handles large datasets and captures non-linear relationships and variable interactions. By training the XGBoost model on founder and financial variables, the study generates high-performing predictions that reflect how these factors combine to influence success probability. SHAP values are then derived from this trained model to break down each prediction into the contribution of individual variables. This approach moves beyond traditional coefficient-based interpretations by quantifying the marginal effect of each feature for each observation, making it possible to see both the average importance and how the influence may vary across startups.

Figure 3.1 SHAP based variable importance of founder and financial indicators

This bar chart shows the average absolute SHAP values for the top variables influencing startup success probability. SHAP values quantify the marginal contribution of each variable to the model's prediction. Higher SHAP values indicate greater impact on the model's output. For detailed variable definitions, see Table 3.2.

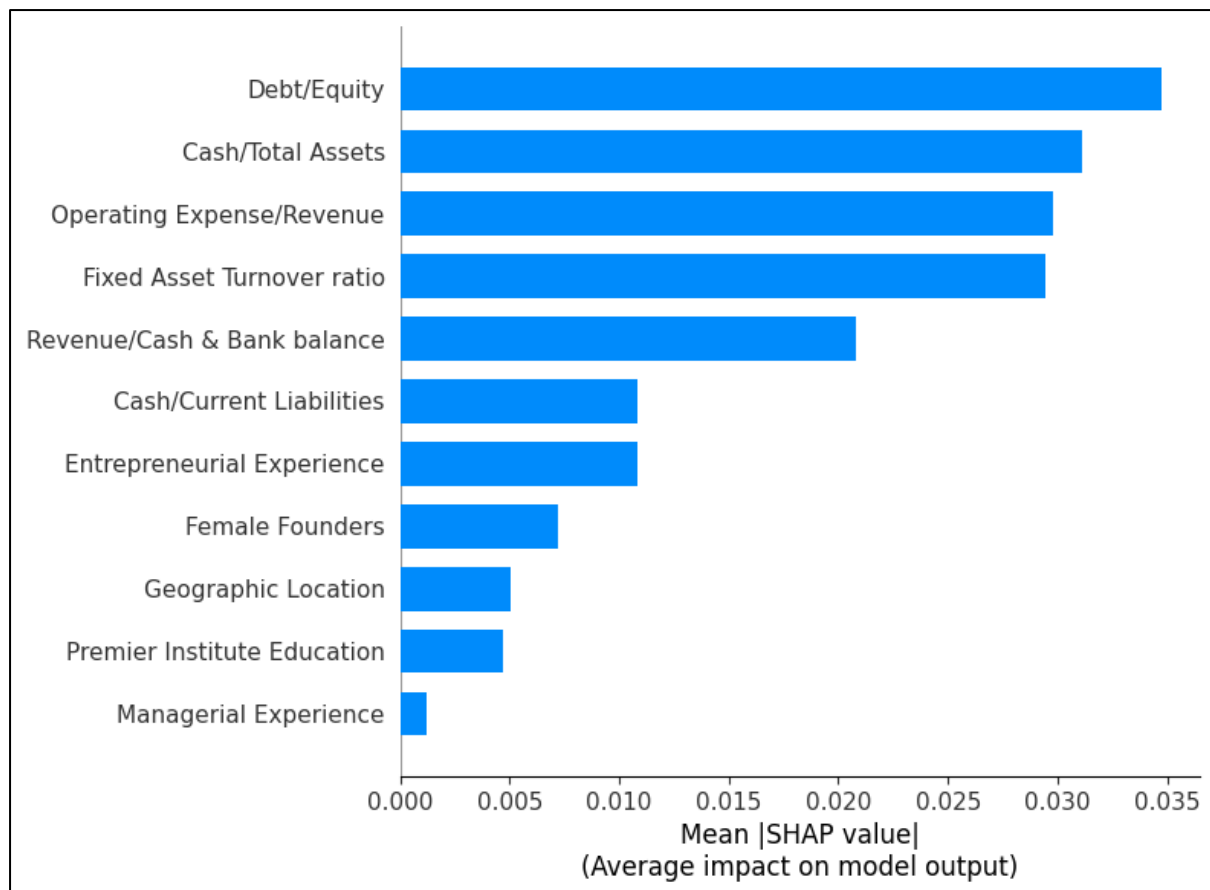


Figure 3.1 shows a SHAP summary bar plot that ranks the variables (founder and financial indicators) by their mean absolute contribution across all observations and helps us to identify the most influential predictors. Consistent with the regression findings, financial variables emerge as the most influential predictors of startup success. In particular, financial leverage indicated by the debt-to-equity ratio, operating efficiency measured by the operating expenses ratio, and liquidity captured by the cash-to-current liabilities ratio stand out as critical determinants. Among the founder-related factors, entrepreneurial experience stands out as the most impactful, while managerial experience shows relatively lower importance, likely due to its limited variation as a binary variable.

3.3.5 Direction and Magnitude of Variables

While the bar plot ranks the variables by average absolute SHAP values and answers “*which factors matter most?*”. It does not reveal the direction and magnitude of each variable. The bee-swarm plot addresses this by plotting each observation’s SHAP value for every feature, making it easy to spot patterns. For example, whether high debt pushes valuation down for most startups, or if the effect of liquidity varies more widely etc. By doing so, the SHAP bee-swarm plot adds important context by visualizing both the *direction* and the *distribution* of each variable’s effect across all individual cases.

In a SHAP bee-swarm plot, each horizontal row represents a variable, and each dot corresponds to a single startup. The x-axis shows the SHAP value, indicating whether the variable increases (right) or decreases (left) the prediction. The color gradient represents the variable's actual magnitude, with red denoting higher values and blue denoting lower values.

Figure 3.2 SHAP Beeswarm plot showing variable direction and magnitude

This SHAP beeswarm plot displays the distribution of SHAP values for each founder and financial indicator, illustrating how individual variable values influence the predicted probability of startup success. Each dot represents a startup observation. Dots are color-coded by the variable value (red = high, blue = low). The plot shows the direction and variability of variable influence across observations. For detailed variable definitions, see Table 3.2.

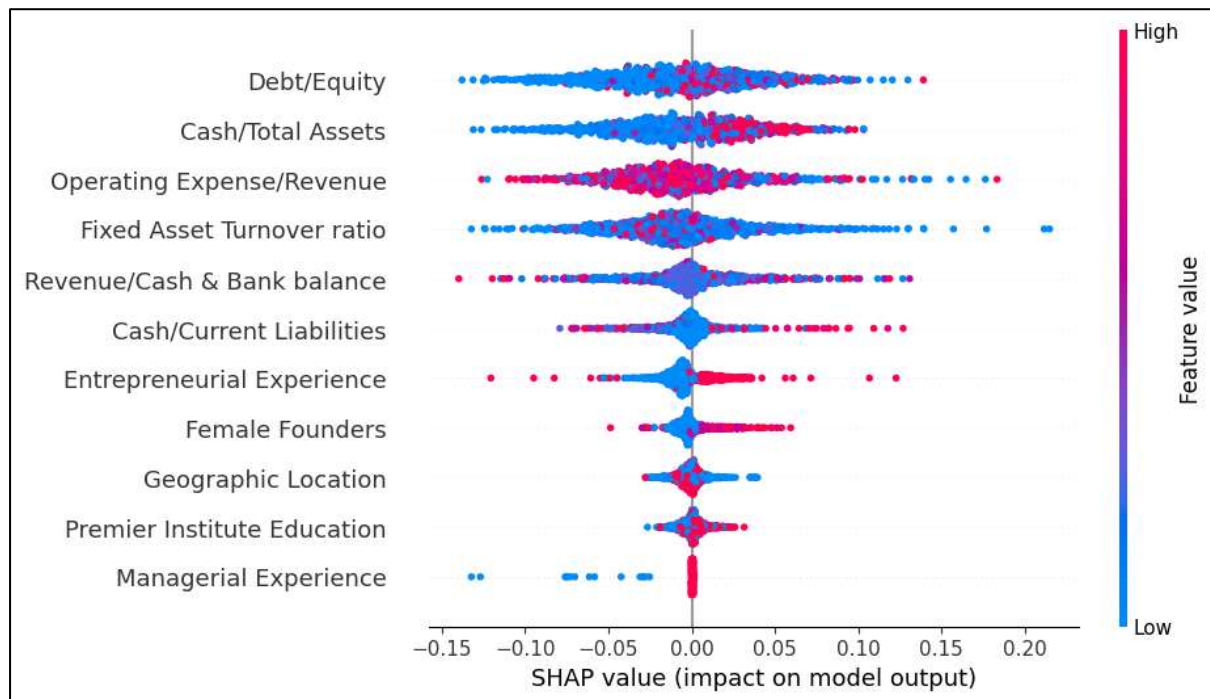


Figure 3.2 shows that the patterns observed are consistent with the beta regression results. For example, startups with higher debt-to-equity (red dots on the right) tend to have higher predicted success probabilities, highlighting the effective management of debt and its signalling capacity. Conversely, a high operating expense-to-revenue ratio (red dots on the left) is associated with lower success predictions, pointing to the negative effect of cost inefficiency. Among founder-related variables, entrepreneurial experience exerts a visible positive impact, whereas managerial experience shows limited variation and correspondingly modest influence.

3.3.6 Interaction of the founder and financial indicators

This section examines how the relative importance of founder and financial factors changes across the startup lifecycle. Rather than looking at individual variables, the study groups the SHAP values from the predictive model into two broad categories: founder-related attributes and financial indicators. For each startup, the group-level SHAP score is calculated by summing the individual SHAP values of all variables within the categories. The study then examines how the relationship between the founder and the financial group evolves as the firm grows. To highlight these dynamics in greater detail, the analysis is presented in two parts: (i) focusing on firm age and (ii) focusing on funding stages.

For the first part of this analysis, firm age is used as a moderator to examine how the effects of founder and financial factors shift as startups progress through their lifecycle. Specifically, an interaction term between firm age and the SHAP scores for each group is created and then run a regression that includes the SHAP group scores, firm age, and the interaction terms. This allows us to test whether the influence of founder-related or financial factors becomes stronger or weaker as startups advances in age.

The results shown in Table 3.6 reveal that both founder and financial signals independently play a positive and significant role in predicting startup success. Notably, the positive and significant interaction between financial factors and firm age suggests that the weight placed on financial performance grows stronger as startups mature. In other words, as ventures progress through their lifecycle, investors increasingly anchor their valuation decisions on tangible financial indicators rather than relying solely on the founders' background or narrative.

Table 3.6 Interaction of founder and financial indicators with firm age

This table reports regression results of the interaction between founder and financial SHAP values and firm age on the probability of startup success. SHAP values represent the model-derived contribution of founder and financial variables to success probability. The interaction terms test whether the influence of founder and financial characteristics varies with firm age. Robust standard errors are reported in parentheses. *** indicates significance at 1% level.

VARIABLES	(1) <i>p</i>
Founder SHAP	1.530*** (0.251)
Financial SHAP	1.448*** (0.042)
Firm age	0.079*** (0.003)
Founder SHAP x Firm age	-0.082 (0.133)
Financial SHAP x Firm age	0.068*** (0.023)
Constant	0.247*** (0.005)
Observations	1100

In contrast, the interaction between founder attributes and firm age, though negative, is not statistically significant, implying that there is no clear evidence that the influence of founder qualities systematically diminishes over time. Together, these findings highlight a dynamic shift: while both the *jockey* and the *horse* matter, the *horse* or the firm's financial health becomes more decisive as the startup moves beyond its formative years.

In addition, this study explores how the interplay between founder characteristics and financial performance shifts as startups move through different stages of funding. To examine this, the average strength of founder and financial interactions for each funding round is calculated. This enables us to examine whether founder qualities and financial indicators work as complimentary or substitutes in predicting startup success through its lifecycle.

Figure 3.3 Founder–Financial SHAP interaction strength across funding rounds

This figure shows the average SHAP interaction values between founder characteristics and financial indicators across different funding rounds. The quadratic fit highlights the non-linear trend. Interaction peaks at Series B, indicating the heightened joint influence of founder and financial factors during mid-stage funding, and decline as performance-based signals gain prominence in later rounds.

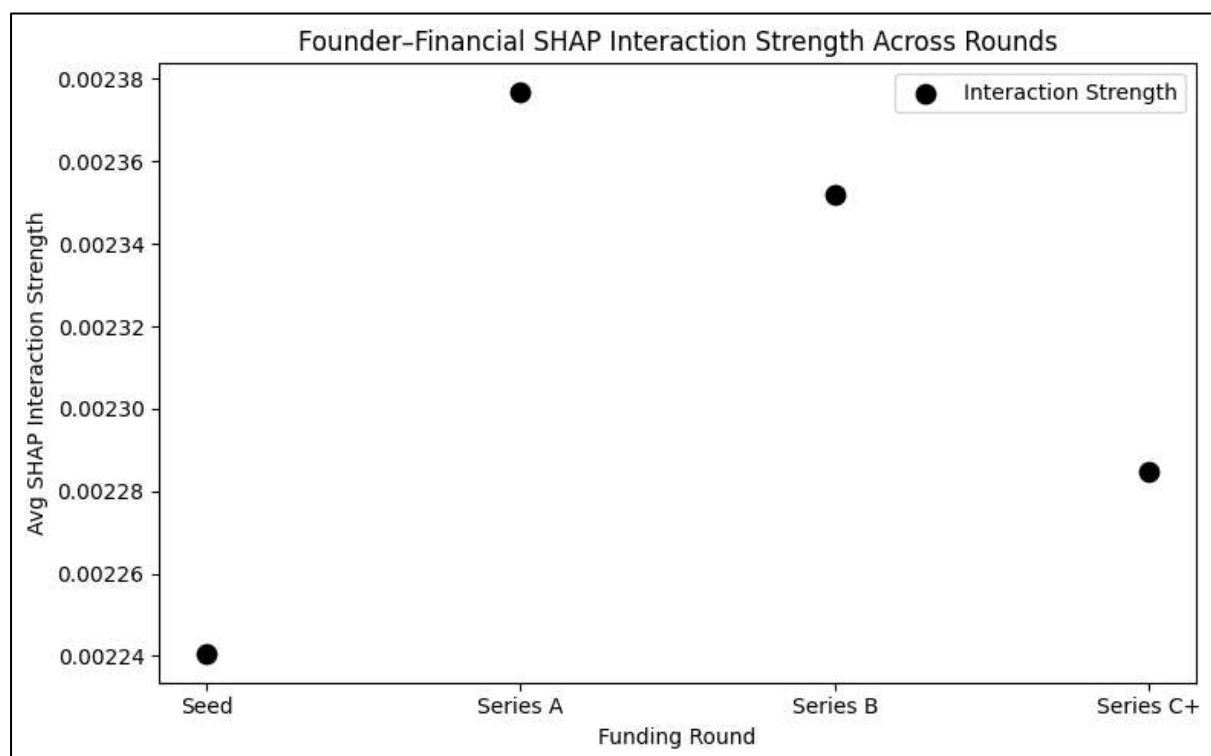


Figure 3.3 plots the interaction value of founder and financial factors on success probability. The quadratic fit highlights the non-linear trend. The figure shows that the interaction strength of the factors becomes stronger through the early and growth stages, peaking around Series B, and then gradually declines in later rounds. This pattern suggests that founder and financial factors are most interdependent during the early to mid-stages of a startup's lifecycle. In later rounds (Series B or beyond), the influence of founder traits declines, and financial indicators become more important, suggesting that a startup's valuation is increasingly determined by measurable financial performance. This reflects a shift towards performance-based valuation.

3.4 Summary of findings and implications

This study examines the observable signals that shape startup valuation, focusing on both founder characteristics and key financial ratios within the *jockey–horse* framework. The results highlight that financial quality plays a critical role in scaling valuations in dynamic, high-risk startup contexts. While it may seem intuitive that financial performance matters, the findings specify which financial indicators matter most: liquidity, leverage, and operating efficiency emerge as particularly influential drivers of valuation growth. The positive interaction between firm age and financial strength further suggests that robust financial fundamentals gain importance as startups mature. Moreover, as ventures progress to later funding stages, especially beyond Series B, the weight shifts from founder-driven narratives to greater emphasis on tangible financial performance, underscoring how the ‘*horse*’ increasingly takes the lead over the ‘*jockey*’ in driving investor confidence and valuation outcomes.

This study offers meaningful contributions to both practice and research. First, unlike much of the existing literature that relies on binary outcomes for entrepreneurial evaluation (Bock and Schmidt, 2015; Gompers et al., 2010; Guo et al., 2015; Nanda et al., 2020; Nguyen and Vo,

2021), this study uses a continuous measure of success probability, which enables a more nuanced analysis of startup growth trajectories over time. Second, the findings provide empirical insights into the key signals of startup success, offering VC investors a practical framework for screening and due diligence. Importantly, it critically examines the role of the *horse*, which has often received less nuanced attention in prior research. The study moves beyond the general idea that 'financials matter' and clarify which aspects of financial quality are critical for scaling valuations in dynamic, high-risk startup contexts. In doing so, this study extend the work of Armstrong et al. (2006), Corea et al. (2021), Hand (2005), Kaplan et al. (2009) and Sievers et al. (2013). Finally, by focusing on India, an emerging market with high uncertainty and evolving institutional support, the study provides contextual insights into how internal firm characteristics operate in resource-constrained environments (Bonini and Capizzi, 2019; Bustamante et al., 2021; Oino, 2014).

Chapter 4

Industry attractiveness and startup valuation

4.1 Introduction

Given the scarcity of detailed historical financial information and the sheer volume of startup applications, VCs often rely on industry-level signals as practical screening tools when selecting potential investments (Que and Zhang, 2021). It is common for VCs to cluster around so-called “hot” sectors, assuming that favourable industry conditions will translate into stronger firm performance. However, there is another school of thought which argues that each startup is fundamentally a unique experiment - a bet not only on a promising sector but also on the founders’ capabilities, the viability of the business model, and the strength of its financial foundations. Even in thriving industries, some startups thrive while others stall. Hence, what sets startups apart is often not the sector they operate in but the strength of their founder’s competence and the financial foundation.

This chapter examines how VCs identify potential winners in the Indian startup ecosystem. Do they rely solely on the attractiveness of the industry? Do firm fundamentals matter more? Or is it the combination of both that guides funding decisions? To examine these dimensions empirically, industry attractiveness (*IA*) is measured using lagged sector-level indicators of profitability, liquidity, and exit opportunities. Firm fundamentals (*Fhealth*) are captured through startup-level metrics reflecting profitability, leverage, liquidity, and operational efficiency.

This analysis is anchored in two key theoretical perspectives: the Market-Based View (MBV) and the Resource-Based View (RBV). The MBV posits that a firm’s valuation is strongly

shaped by external conditions, such as industry structure and market dynamics (Peteraf and Bergen, 2003), whereas the RBV contends that internal capabilities and resources including financial health, operational efficiency, and managerial strength are critical drivers of firm success (Terziovski, 2010). By analysing the relative weight of industry conditions versus firm-specific strengths, this chapter provides deeper insight into how valuation is shaped in high-growth contexts and sheds light on the strategic logic underpinning VC investment choices in emerging markets.

The chapter is structured as follows: Section 4.2 outlines the data and model specifications; Section 4.3 presents the empirical results; and Section 4.4 offers a summary and concluding remarks.

4.2 Data and Method

4.2.1 Data Sources and Sample Selection

This study uses data on Indian startups that received VC funding across stages ranging from Seed to Series J. The sample is restricted to startups founded between January 1, 2000, and December 31, 2020. Startup-level data, including financials and valuation information, is sourced from Tracxn, a leading startup intelligence platform. To ensure data quality and consistency, firms with missing information on post-money valuation or key financial variables were excluded. The final sample comprises 675 funding rounds. The sample distribution is described in Table 4.1.

Table 4.1 Sample distribution

This table summarises the sample distribution across three dimensions: Panel A shows the industry-wise breakdown of firms, Panel B presents the distribution by founding year cohorts, and Panel C reports the number of funding rounds by stage. The dataset includes 322 startups and a total of 675 funding rounds, reflecting diversity in industry, firm age, and funding stage.

Panel A: Industry-wise sample distribution	
Industry	Number of firms
Edtech	26
Fintech	55
Health & services	28
IT & Services	35
Retail	52
Others	126
Total	322

Panel B: Year-wise sample distribution	
Year	Number of firms
2000-2005	14
2006-2010	63
2011-2015	144
2016-2020	101
Total	322

Panel C: Funding round-wise distribution	
Round name	Number of funding rounds
Seed	176
Series A	206
Series B	124
Series C	79
Series D+	90
Total	675

Industry-level data used to construct measures of industry attractiveness is obtained from EMIS (Emerging Markets Information Service). This includes sectoral indicators such as return on invested capital (ROIC), mergers and acquisitions (M&A) activity, and initial public offerings

(IPO) activity. Industries are classified based on two-digit SIC codes, allowing for standardized comparison across sectors.

4.2.2 Variable description

All variables used in the analysis are listed in Table 4.2. Details on the construction and measurement of each variable are provided in the following sections.

Table 4.2 Variable definitions

This table details variable definitions used in this study

Variable	Description
<i>Valuation</i>	Natural log of post-money valuation of the firm in a funding round.
<i>Industry attractiveness (IA)</i>	Standardized Z-score based on lagged industry ROIC, MandAs, and IPOs. See Table 4.3 for further details.
<i>Financial Health (FHealth)</i>	Adapted F-score based on firm profitability, liquidity/leverage and operational efficiency. See Table 4.4 for further details.
<i>Syndication</i>	Natural log of the total number of investors in a funding round.
<i>Firm age</i>	Natural log of the difference between the funding year and the firm founded year.
<i>Funding rounds</i>	Natural log of the number of previous funding rounds plus one.
<i>Geographic location</i>	Dummy variable equal to one if the startup firm is located in the startup hub or otherwise equal to zero, where startup hubs are the top four startup locations in India (Bengaluru, Mumbai, Delhi, and Hyderabad).

4.2.2.1 Dependent Variable

In this study, startup valuation is the focal dependent variable, reflecting the perceived worth of a venture at each stage. Valuation is captured through the natural logarithm of the post-money valuation reported for each funding round. Taking the logarithm helps address the inherent skewness in raw valuation figures, which often vary widely across startups and funding stages.

4.2.2.1 Industry Attractiveness (IA)

The first key explanatory variable is Industry Attractiveness (IA), operationalized as a standardized Z-score derived from three lagged industry-level indicators - Return on Invested Capital (ROIC), M&A market liquidity of the industry, and IPO activity of industry. The construction of IA components is listed in Table 4.3.

Table 4.3 Composition of industry attractiveness

This table details the components used to construct the industry attractiveness (IA) measure. IA is computed as a standardized Z-score based on these three industry-level factors and each component is measured at the industry level for the year preceding the observation (t-1).

Variable	Description
Lagged ROIC	The cross-sectional annual estimate of an industry's profitability for industry j in the year $t-1$
Lagged M&A	The liquidity of MandAs is captured by the ratio of the aggregate value of corporate transactions to the total book value of assets for each industry j in year $t-1$
Lagged IPO	The natural logarithm of the number of IPOs of venture-backed companies in industry j in year $t-1$

Lagged M&A: Liquidity for each industry is assessed using the M&A market liquidity metric defined by Nguyen and Vo (2021), Ortiz-Molina and Phillips (2014) and Sibilkov (2009). It is computed as the ratio of the aggregate value of corporate transactions to the total book value of assets for each industry year. Following Sibilkov (2009), this study include only value-disclosed transactions, encompassing leveraged buyouts, tender offers, spinoffs, exchange offers, stake purchases, and privatisations, all with a value equal to or exceeding one million USD. Industries are categorised based on the first two digits of SIC codes in the Refinitiv database, and transaction values are aggregated at the industry-year level. Then the final metric

defined as M&A market liquidity is computed by dividing the total value of corporate transactions by the total book value of assets listed in EMIS for each industry year. *Lagged M&A* represents the liquidity of the M&A market for an industry at the time, $t-1$.

Lagged ROIC: Industry profitability, as defined by Patel et al. (2020) and Olson and Pagano (2017), is gauged through return on invested capital (*ROIC*), a cross-sectional annual estimate of an industry's profitability. *ROIC* is computed for each industry by regressing the net operating profit after tax (NOPAT) of each firm on the firm's lagged total capital. NOPAT is the difference between earnings before interest, taxes, depreciation, and amortisation (EBITDA) and income taxes paid for the year, and lagged total capital is the sum of the book value of long-term debt, common stock, and preferred stock for the i -th company at the time, $t-1$ (Olson and Pagano, 2023). The yearly accounting and equity market capitalisation data utilised for estimation are sourced from EMIS. The study considers *Lagged ROIC*, which is the ROIC for an industry at the time, $t-1$.

Lagged IPO: *Lagged IPO* is the natural logarithm of the number of IPOs of venture-backed companies in industry j in year $t-1$ (Gompers et al., 2008). Refinitiv provides data on the IPOs of VC-backed firms.

To construct *IA*, these three lagged industry-level indicators are combined into a single score. First, each indicator was winsorised at the 1st and 99th percentiles to reduce the influence of extreme outliers. Then, each variable is standardized by converting it into a Z-score (subtracting the mean and dividing by the standard deviation) within each year. Finally, the *IA* index for each industry-year is computed by taking the simple average of the three standardized lagged scores. The estimation equation is given as follows;

$$IA_{jt} = \frac{Z-AL_{j,t-1} + Z-IPO_{j,t-1} + Z-ROIC_{j,t-1}}{3} \quad (4.1)$$

When combining multiple indicators with different units or scales (e.g., M&A liquidity ratio and IPO count as a natural log of the count), directly averaging the raw values is misleading. Z-score standardization transforms each indicator onto the same scale, so each contributes equally to the index. This approach is transparent and avoids arbitrary weighting. Using lagged values ensures that the index reflects industry conditions as they would have been known to investors and hence avoids any forward-looking bias. The resulting IA score provides a comparable, standardized measure of how attractive an industry is for startups in any given year. Industry classifications follow the two-digit National Industrial Classification (NIC) code to ensure consistency when aggregating sector-level data.

4.2.2.2 *Financial Health (FHealth)*

The second key explanatory variable is Financial Health (*FHealth*), which is a startup-specific adaptation of Piotroski's F-score (Piotroski, 2000). The original F-score was designed for publicly listed firms with stable earnings, predictable cash flows, and standardized financial disclosures. Venture-backed startups, by contrast, operate under markedly different conditions, characterised by rapid growth, heavy reinvestment, volatile earnings, and frequent financing events. Consequently, direct application of the original F-score would obscure rather than capture meaningful variation in startup financial quality. To address this, each component of the score is modified to reflect how financial health manifests in early-stage firms. Table 4.4 presents the detailed mapping between the original and adapted measures.

In the profitability dimension, traditional metrics such as net income and return on assets are replaced because they often penalise startups for growth-oriented investment rather than poor performance. Many startups report accounting losses even when underlying operations are improving. For this reason, profitability is assessed using positive EBIT (earnings before interest and taxes), which isolates operating performance from financing decisions. Instead of a static profitability measure, growth in EBIT margin is used to capture whether the startup is becoming more efficient over time, signalling progress toward sustainable operations. Operating cash flow is replaced with year-over-year growth in cash and bank balances, as formal cash flow statements are frequently unavailable or unreliable for young firms. Changes in cash holdings provide a practical and observable proxy for underlying cash flow strength in this setting.

The liquidity and leverage components are adapted to emphasise short-term financial resilience, which is critical for startup survival. Rather than focusing on reductions in total debt, which may not be meaningful when debt is used as a flexible financing instrument, the adapted framework evaluates whether the startup holds sufficient liquid resources to meet current liabilities and financing costs. Cash-based coverage ratios are therefore employed, as they directly capture the firm's ability to sustain operations during periods of revenue volatility. The original criterion of "no equity issuance" is also modified, as equity financing is a normal and often necessary part of startup growth. Instead, the adapted measure flags excessive dilution by focusing on whether equity share capital growth exceeds a defined threshold, distinguishing healthy fundraising from over-reliance on external equity.

Operational efficiency measures are similarly revised to reflect the scaling dynamics of startups. Gross margin and asset turnover assume stable production technologies and mature asset bases, which are less applicable to rapidly evolving firms. A declining operating expense

ratio is therefore used to assess whether the startup is achieving economies of scale and improving cost discipline as it grows. Revenue relative to fixed assets captures how effectively the firm converts capital investment into sales, which is a more relevant indicator of efficiency in capital-constrained, high-growth environments.

Overall, these adaptations retain the conceptual structure of Piotroski's F-score while systematically replacing public-firm-oriented metrics with startup-relevant indicators. The resulting FHealth score offers a coherent and context-sensitive measure of financial discipline, liquidity strength, and operational efficiency, providing a more accurate assessment of financial health in venture-backed startups.

Table 4.4 Adapted F-score composition

This table details the composition of the Adapted F-Score, which is a startup-specific financial health indicator based on Piotroski's (2000) F-Score framework. The Adapted F-score is the sum of all the components and has a range from zero to eight.

Category	Original Metric	Startup Adaptation	Formula
Profitability	Positive net income	Positive EBIT	$EBIT > 0$
	Positive ROA	EBIT margin growth	$EBIT \text{ margin (Current)} > EBIT \text{ margin (Previous year)}$
	Positive operating cash flow	Cash flow strength	$Cash \text{ and bank balance} > \text{Previous year}$
Liquidity/Leverage	Declining debt	Liquidity coverage ratio	$Cash \text{ and bank} > \text{Current liabilities}$
	Increasing current ratio	Cash coverage ratio	$Cash / \text{Finance cost} > 1$
	No equity issuance	No major dilution	$Equity \text{ share capital growth} < 10\%$
Operational Efficiency	Higher gross margin	Lower operating expense ratio	$Operating \text{ expense ratio} < \text{Previous operating expense ratio}$
	Higher asset turnover	Revenue per fixed asset	$Revenue / \text{Fixed assets} > 1$

4.2.2.3 *Control Variables*

To account for factors that have been shown to systematically influence startup valuation, several controls are included in the analysis. Prior research suggests that syndication is typically associated with higher valuations, as rounds involving multiple investors can signal quality and reduce information asymmetries through shared due diligence and reputational monitoring (Lerner, 1994; Manigart et al., 2006). Firm age is included since older startups may benefit from greater credibility and operational maturity (Davila et al., 2003; Gompers et al., 2008). The number of previous funding rounds generally correlates with higher valuations, reflecting sustained investor interest, demonstrated traction, and the signaling effect of prior successful financing (Kaplan and Strömberg, 2003; Chemmanur et al., 2011). Geographic location also matters, as startups situated in major hubs tend to attract higher valuations due to better access to networks, capital, talent, and supportive entrepreneurial ecosystems (Saxenian, 1994; Mason and Harrison, 2002). Including these variables helps to control for these well-established influences and to better isolate the effects of the main explanatory factors of interest.

In addition, industry dummies, based on two-digit SIC codes, are included to control for unobserved sector-specific characteristics that may systematically influence valuation, such as differences in capital intensity, growth opportunities, or typical exit conditions across industries (Hsu, 2004; Tian, 2011). Year fixed effects are also incorporated to account for time-varying macroeconomic factors, policy shifts, or broader market cycles that could affect startup valuations across all firms in a given year (Kaplan and Lerner, 2016). Together, these controls help ensure that the estimated effects of the key explanatory variables are not confounded by industry structure or temporal shocks.

4.2.3 Analytical Approach

This study examines how Industry Attractiveness (*IA*) relates to startup valuations and whether this relationship is influenced by a firm's financial health (*FHealth*). First, a mean comparison is conducted to provide initial evidence of how valuations differ between startups operating in more attractive versus less attractive industries.

Next, to test for potential non-linearity in the *IA*–valuation relationship, *IA* is modelled using a cubic polynomial specification. This approach allows the marginal effect of *IA* on valuation to vary across its range and helps detect possible inflection points where the direction or strength of the relationship may change.

To further capture possible localized variations that a global polynomial may smooth over, a spline regression is estimated as an additional check. The piecewise polynomial (spline) model partitions the *IA* variable into intervals and fits separate polynomial functions within each segment. This flexible approach allows the slope of the *IA*–valuation relationship to change at specified knots, highlighting whether industry attractiveness exerts different effects at lower, middle, or higher ranges.

Finally, to test whether the effect of *IA* on valuation depends on a startup's financial fundamentals, a multiple linear regression model is estimated with an interaction term between *IA* and *FHealth*. This specification assesses whether startups with stronger financial indicators benefit differently from operating in attractive industries compared to those with weaker fundamentals. Control variables for syndication, firm age, prior funding rounds, geographic location, industry dummies, and year fixed effects are included to account for observable heterogeneity and macroeconomic factors that could confound the results.

Together, this multi-stage empirical design combines descriptive evidence, non-linear modeling, and interaction evaluation to provide a robust examination of how industry context and firm-level financial strength jointly shape startup valuations.

4.3 Results

4.3.1 Descriptive statistics

Table 4.5 reports the descriptive statistics for the main variables used in the analysis. The mean startup valuation shows considerable variation across firms. Industry Attractiveness (*IA*) has a mean of 0.00 because it is a standardized Z-score composite; this centering around zero is expected. The *IA* descriptive statistics show a median of -0.16 and an interquartile range from -0.35 to 0.43, suggesting that most firms are in moderately attractive industries. Financial health (*FHealth*) has a mean of 4.11 and median of 4.00 with a standard deviation of 1.48, indicating a fairly symmetric spread around the central value.

Table 4.5 Descriptive statistics - *IA*, *Fhealth* and other controls

This table reports the mean, median, and standard deviation (SD) for the key variables used in the analysis. See Table 4.2 for variable definitions. The sample consists of 675 funding rounds between 2000 and 2020. *IA* represents industry attractiveness as given in 4.2.2.1 and *Fhealth* indicates financial health as given in 4.2.2.2. The nature of other variables are provided in the brackets.

	obs	mean	std	25%	50%	75%
<i>Valuation (ln)</i>	675	3.46	1.89	2.14	3.28	4.66
<i>Industry attractiveness (IA)</i>	675	0.00	0.63	-0.35	-0.16	0.43
<i>Financial health (FHealth)</i>	675	4.11	1.48	3.00	4.00	5.00
<i>Investor syndication (ln)</i>	675	1.56	0.79	0.90	1.39	2.08
<i>Funding rounds (ln)</i>	675	1.48	0.58	1.10	1.39	1.95
<i>Firm age (ln)</i>	675	1.63	0.63	1.10	1.61	2.08
<i>Geographic location (binary)</i>	675	0.66	0.47	0.00	1.00	1.00

4.3.2 Industry attractiveness and valuation

The mean comparison of startup valuations across high and low *IA* groups indicates that contrary to conventional expectations, firms operating in high *IA* industries have significantly lower average valuations than those in low *IA* industries. Table 4.6 reports that the mean valuation for high *IA* firms (3.21) is significantly lower than for low *IA* firms (3.82), the mean difference is statistically significant at 1%. This finding provides initial evidence that industry-level attractiveness may not have a linear relationship with higher firm-level valuations in emerging markets.

Startups are divided into high and low *IA* groups based on a median split of the *IA* index. Mean post-money valuations for these groups are then compared to identify whether observable differences exist as shown in Table 4.6. This descriptive step helps establish baseline patterns before applying more formal estimation techniques.

Table 4.6 Valuations between high and low industry attractiveness

This table presents the results of a two-sample *t*-test comparing the valuations between firms in high and low industry attractiveness (*IA*) groups. See Table 4.2 for variable definitions. Firms are classified into high and low *IA* based on a median split of the *IA* variable. The sample consists of 675 funding rounds between 2000 and 2020. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively.

Variable	High <i>IA</i> Mean	Low <i>IA</i> Mean	Difference	<i>p</i> -value
Valuation	3.207	3.817	-0.611	-0.0001***

To further examine this dynamic relationship, *IA* is modelled as a continuous variable using a cubic polynomial regression, controlling for key firm characteristics and fixed effects. As shown in Table 4.7, a unique non-linear and statistically significant relationship between *IA* and startup valuation is evident: valuation initially declines with increasing *IA* (i.e., see *IA*

coefficient estimate), rises at moderate levels (i.e., see IA^2 coefficient estimate), and declines again at very high levels (i.e., see IA^3 coefficient estimate).

Table 4.7 Industry attractiveness and startup valuation

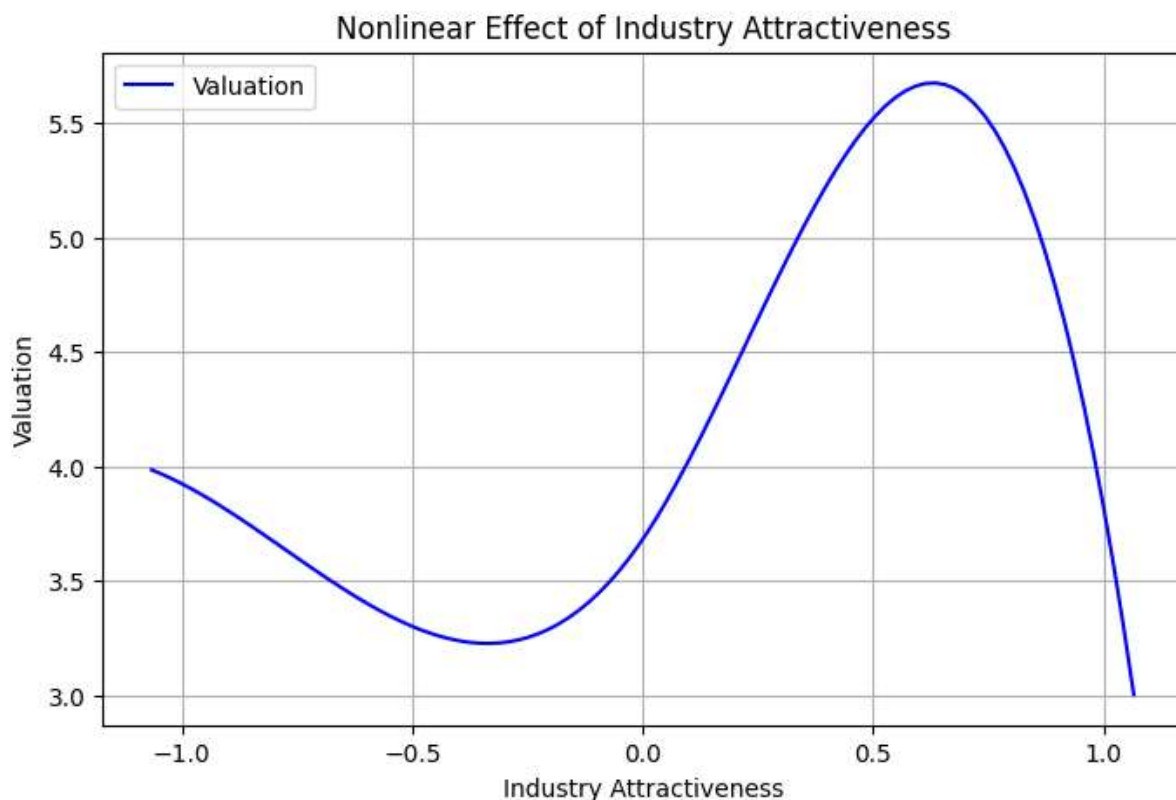
This table reports cubic polynomial regression results estimating the impact of *industry attractiveness* (IA), including its cubic terms, on startup valuation. See Table 4.2 for variable definitions. The sample consists of 675 funding rounds between 2000 and 2020. Robust standard errors are reported in parentheses. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively.

Variables	Model 1 <i>Valuation</i>	Model 2 <i>Valuation</i>	Model 3 <i>Valuation</i>	Model 4 <i>Valuation</i>
IA	-0.564*** (0.178)	-0.532*** (0.187)	-0.482** (0.199)	-0.434** (0.215)
IA^2	0.732*** (0.265)	0.856*** (0.273)	0.656** (0.274)	0.793*** (0.284)
IA^3	-0.123*** (0.048)	-0.152*** (0.05)	-0.110** (0.049)	-0.143*** (0.052)
<i>Investor syndication</i>	-0.020*** (0.007)	-0.019*** (0.007)	-0.018** (0.007)	-0.017** (0.007)
<i>Funding rounds</i>	1.844*** (0.112)	1.823*** (0.115)	1.821*** (0.111)	1.815*** (0.113)
<i>Firm age</i>	0.389*** (0.104)	0.427*** (0.104)	0.423*** (0.104)	0.453*** (0.104)
<i>Geographic location</i>	(0.04) (0.116)	(0.035) (0.115)	(0.053) (0.116)	(0.054) (0.115)
<i>Constant</i>	0.101 (0.194)	0.049 (0.202)	0.092 (0.195)	0.029 (0.204)
N	675	675	675	675
R^2	0.444	0.469	0.47	0.494
$Adj. R^2$	0.438	0.457	0.46	0.478
Industry FE	No	No	Yes	Yes
Year FE	No	Yes	No	Yes

The study uses a spline regression model, which breaks the predictor into different ranges and fits separate smooth curves to each range. This approach allows the relationship between the predictor and the outcome to change gradually across different intervals, capturing any shifts or bends that a single straight line or polynomial might miss. Figure 4.1 plots the fitted values from the spline regression model that highlights intervals where the effect strengthens, weakens, or even reverses direction.

Figure 4.1 Spline plot of industry attractiveness and startup valuation

This figure presents a spline plot capturing the relationship between industry attractiveness (*IA*) and startup valuation, allowing for smooth, flexible variation across different levels of *IA*. The plot is based on a sample of 675 VC-funded startup rounds in India between 2000 and 2020.



It is important to note that, when considering observations at the upper tail of the *IA* distribution, the relationship takes the form of an inverted S-shape. This implies that moderate

improvements in industry attractiveness tend to support higher startup valuations, but at very high levels of attractiveness the benefits taper off. Industries that are “too attractive” becomes crowded, competitive, or overheated, thereby reducing the marginal advantage to individual startups.

Collectively, the findings indicate that industries face natural limits on how much their attractiveness drives the firm valuations. These findings are consistent with the Industry Life Cycle (ILC) theory which implies that industries evolve through a series of predictable stages over time, each with distinct characteristics in terms of competition, innovation, growth, and firm behavior (Borda, 2023). During early growth phases, higher *IA* leads to rising valuations. But as the industry matures, competition intensifies, growth slows, and returns diminish, resulting in a non-linear relationship between *IA* and valuation.

4.3.3 Industry attractiveness, financial health and valuation

Next, the study examines the combined influence of *IA* and firm-level financial fundamentals (*FHealth*) on startup valuation. The regression model is specified as follows;

$$Valuation_{j,s} = \alpha + \beta (IA)_j + \delta (FHealth)_{j,s} + \sum_k y_k Controls_{j,s,k} + \epsilon_{j,s} \quad (4.2)$$

In this model, $Valuation_{j,s}$ denotes the valuation of startup j in funding round s . The specification examines how industry attractiveness (*IA*), firm financial health (*FHealth*), and other control variables jointly influence the valuation outcome. $\sum_k y_k Controls_{j,s,k}$ accounts for additional control variables that may affect valuation, such as deal characteristics, investor type, or firm age. $\epsilon_{j,s}$ is the error term that absorbs unobserved factors influencing the valuation of the startup.

The results of the regression analysis are reported in Table 4.8.

Table 4.8 Industry attractiveness, financial health and startup valuation

This table reports regression results estimating the impact of *industry attractiveness (IA)*, and *financial health (FHealth)*, on startup valuation. See Table 1 for variable definitions. The sample consists of 675 funding rounds between 2000 and 2020. Standard errors clustered by firm are reported in parentheses. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively.

Variables	Model 1 <i>Valuation</i>	Model 2 <i>Valuation</i>	Model 3 <i>Valuation</i>
<i>IA</i>	0.171* (0.103)		0.529** (0.213)
<i>FHealth</i>		0.069* (0.037)	0.049* (0.027)
<i>IA x FHealth</i>			-0.124** (0.052)
<i>Investor syndication</i>	-0.019*** (0.007)	-0.015** (0.007)	-0.010** (0.005)
<i>Funding rounds</i>	1.864*** (0.113)	1.694*** (0.117)	1.521*** (0.161)
<i>Firm age</i>	0.387*** (0.105)	0.429*** (0.109)	0.422** (0.184)
<i>Geographic location</i>	-0.030 (0.117)	-0.094 (0.115)	
<i>Constant</i>	0.203 (0.191)	0.690*** (0.243)	0.800*** (0.171)
N	675	675	675
R^2	0.437	0.532	0.931
$Adj. R^2$	0.433	0.418	0.897
Industry FE	No	Yes	No
Startup FE	No	No	Yes

The results presented in Table 4.8 show that industry attractiveness (IA) and financial health (FHealth) both have a positive and significant effect on startup valuation when considered separately (Models 1 and 2). However, the significant negative interaction term in Model 3 indicates a substitutive relationship: the positive effect of IA diminishes for firms with stronger financial fundamentals.

Building on Steigenberger and Wilhelm's (2018) argument that signals are interpreted in relation to one another, particularly in young and ambiguous markets, our study offers a

different perspective on how such interdependence unfolds. Whereas prior research has often portrayed signals as mutually reinforcing, producing additive benefits when combined (e.g., Vanacker et al., 2020), our evidence points to a substitutive effect. Strong firm-level signals appear to reduce investors' reliance on industry-level cues, just as strong industry conditions can lessen the salience of firm-specific indicators. Our findings are also consistent with Maxwell et al. (2011); given cognitive and resource constraints, VCs tend to focus either on industry or on firm-specific information. This suggests that venture capitalists apply a compensatory logic in their evaluations, balancing across domains rather than simply rewarding the accumulation of multiple signals.

Among the controls, the number of previous funding rounds and firm age are consistently positive and highly significant, suggesting that investor confidence and firm maturity are strong predictors of higher valuations. Interestingly, investor syndication shows a small but significant negative relationship with valuation, similar to that in the previous chapter. The inclusion of industry and startup fixed effects across models further supports the robustness of these findings by accounting for unobserved heterogeneity.

4.3.4 Robustness

For robustness, the analysis is further extended by splitting the sample into young and mature startups. The subsample results, presented in Table 4.9, show that the resource-based view (RBV) holds more strongly for mature firms, where firm-specific financial health has a clearer impact on valuation. In contrast, for younger startups where tangible assets are limited and information asymmetries are greater, industry attractiveness plays a more prominent substitutive role, providing investors with an external signal to assess value in the absence of rich firm-level information.

Table 4.9 Industry attractiveness, financial health and startup valuation - Young and mature startups

This table reports regression results estimating the impact of *industry attractiveness (IA)*, and *financial health (FHealth)*, on startup valuation for the young and mature startups. See Table 4.2 for variable definitions. Models 1 to 3 subsample of young startups and Models 4 to 6 subsample of mature startups, where young startups are four years old or less. The sample consists of 675 funding rounds between 2000 and 2020. Standard errors clustered by firm are reported in parentheses. ***, **, * indicates significance at 1%, 5% and 10% levels, respectively.

Variables	Young			Mature		
	Model 1 <i>Valuation</i>	Model 2 <i>Valuation</i>	Model 3 <i>Valuation</i>	Model 4 <i>Valuation</i>	Model 5 <i>Valuation</i>	Model 6 <i>Valuation</i>
<i>IA</i>	0.457** (0.177)		0.539* (0.317)	0.033 (0.121)		0.267 (0.343)
<i>FHealth</i>		0.162*** (0.057)	0.024 (0.034)		0.063* (0.047)	0.027 (0.038)
<i>IA x FHealth</i>			-0.124* (0.072)			0.065 (0.092)
<i>Investor syndication</i>	-0.022** (0.011)	-0.018* (0.010)	-0.016* (0.008)	-0.020** (0.010)	-0.014 (0.010)	-0.012 (0.009)
<i>Funding rounds</i>	2.235*** (0.153)	1.959*** (0.168)	1.515*** (0.149)	1.530*** (0.147)	1.505*** (0.141)	1.870*** (0.117)
<i>Firm age</i>	0.104 (0.178)	0.151 (0.181)		0.020 (0.149)	0.003 (0.144)	
<i>Geographic location</i>	0.478 (0.294)	1.645*** (0.419)	1.913*** (0.316)	0.992*** (0.223)	0.724** (0.299)	0.475** (0.206)
<i>Constant</i>	0.457** (0.177)		0.539* (0.317)	0.033 (0.121)		0.267 (0.343)
N	331	331	331	344	344	344
R^2	0.404	0.528	0.955	0.257	0.412	0.906
$Adj. R^2$	0.396	0.485	0.931	0.248	0.368	0.843
Industry FE	No	Yes	No	No	Yes	No
Startup FE	No	No	Yes	No	No	Yes

4.4 Summary of findings

This study examines the interplay of industry-level signals and firm-specific financials in influencing startup valuation in one of the fastest-growing startup markets. The results indicate that higher *IA* does not consistently translate to higher firm valuation. In less attractive industries, sound financial fundamentals become a critical factor that enables firms to outperform competitors and achieve higher valuations. These findings will be of interest to local and global VC investors.

By constructing a composite Industry Attractiveness (*IA*) index and an adapted F-Score tailored to the realities of young ventures, this study ensures that broader market conditions and firm-specific fundamentals are captured in ways that reflect startup realities. The study demonstrates that the relationship between industry attractiveness and startup valuation is contingent on firm-specific financial strength, reflecting the logic of the Resource-Based View (RBV). The findings show that while favorable industry conditions can signal growth potential, they do not automatically guarantee higher valuations if a startup lacks strong internal financial fundamentals. In less attractive industries, robust financial health becomes especially critical, allowing firms to offset weaker external signals and secure investor confidence. This substitutive relationship supports the RBV perspective that unique firm-level resources and capabilities remain central to value creation, even in dynamic markets. These insights have practical implications for venture capital investors, who should balance external industry signals with careful assessment of a firm's financial discipline and internal capabilities. For founders and policymakers, the results highlight the importance of strengthening internal financial resilience to attract funding, particularly when operating in industries with lower baseline attractiveness.

Chapter 5

VC investor overconfidence and startup valuation

5.1 Behavioural perspective on firm valuation

Venture capitalists (VCs) are regarded as experts in identifying and funding high-growth startups (Zacharakis and Shepherd, 2001). They play a critical role in shaping the growth trajectories of new ventures and driving innovation within broader entrepreneurial ecosystems. Their ability to assess risk, evaluate market potential, and provide strategic guidance makes them key players in the startup landscape (Bustamante et al., 2021). However, specialized knowledge in a field makes cognitive biases less noticeable and more challenging to overcome (Hoffrage, 2022). VCs, as highly specialized investors, are particularly susceptible to this phenomenon. Their deep industry knowledge and experience may lead to overconfidence in their judgment, reinforcing biases in investment decisions.

A behavioural tendency observed across various investment contexts is that overconfident investors often overestimate their ability to identify high-growth opportunities while underestimating the associated risks. This thesis explores whether similar patterns hold true in the venture capital setting, where high uncertainty and information asymmetry can amplify such biases and explores whether there are any inherent checks and balances within the VC ecosystem that help moderate their effects. This study seeks to address two key research questions: (i) How does venture capital investor overconfidence influence the valuation of the startups they fund? (ii) Can investor syndication moderate this relationship by reducing the effects of overconfidence on valuation?

The intersection of firm valuation and investor overconfidence remains an underexplored area of research. Inflated valuations distort exit expectations, fundraising cycles, and even public

market performance. Given its far-reaching implications, exploring the behavioral patterns of VC investors is essential because they not only affect the firms they invest in but also market dynamics, valuation trends, and overall capital market efficiency.

5.2 Data and Methodology

5.2.1 Sample and Data Source

This study utilizes investment data from Refinitiv to construct the VC Overconfidence Index (OC Index), following the methodology outlined by Amor and Kooli (2024). The primary dataset on startups and their post-money valuations is sourced from Tracxn, a widely recognized database that tracks startup funding activities. The dataset comprises 509 funding rounds of Indian startup firms established between 2000 and 2020, providing a comprehensive view of investment trends over two decades. The sample distribution is described in Table 5.1

The study acknowledges the challenges associated with VC data availability, particularly in identifying lead investors and disaggregating individual contributions within a syndicate. Despite these constraints, the dataset offers a valuable foundation for examining the role of behavioural biases in venture capital investment. Using multiple data sources allows for a comprehensive assessment of VC firm characteristics, investment syndication, and firm-specific factors.

Table 5.1 Sample distribution

This table presents the sample distribution. Panel A shows the number of firms across different industries, while Panel B reports the distribution of firms across four founding year periods. The total sample includes 509 startup firms.

Panel A: Industry-wise sample distribution	
Industry	Number of firms
IT and Software	99
Fintech and services	86
Retail trade	70
Health tech	44
Ed-tech	37
Automobile	23
Others	150
Total	509

Panel B: Year-wise sample distribution	
Year	Number of firms
2000-2005	75
2006-2010	172
2011-2015	172
2016-2020	90
Total	509

Table 5.1 presents the industry-wise and year-wise distribution of the 509 funding rounds analyzed in this study. Panel A provides an industry-wise breakdown, highlighting the sectoral composition of the sample. The IT and software sector accounts for the largest share, with 99 firms, followed by Fintech and services (86 firms) and Retail Trade (70 firms). The *Others* category, which includes diverse industries such as manufacturing, logistics, and energy, comprises 150 firms, reflecting the heterogeneity of the startup ecosystem in the country.

Panel B presents the year-wise distribution of the sample, categorizing firms based on the period in which they received funding. The data spans from 2000 to 2020, capturing evolving investment trends over two decades. The periods 2006–2010 and 2011–2015 represent the most active funding years of the sample, with 172 firms each, reflecting a surge in venture capital activity during these periods.

This distribution underscores the sectoral diversity and temporal evolution of venture capital investments in India, providing a comprehensive sample for analyzing the impact of investor overconfidence on startup valuation across different industries and investment cycles.

5.2.2 *Measuring investor overconfidence*

Overconfidence is considered a multidimensional cognitive bias. Hence, combining different proxies is essential in constructing a robust measure to represent overconfidence. This study adopts the overconfidence index created by Amor and Kooli (2024), considering the specific features of VC investors as given in Table 5.2.

Table 5.2 Overconfidence index components

This table outlines the elements used to construct the overconfidence index for VC investors, based on the approach proposed by Amor and Kooli (2024).

VC venturing experience	The number of years between a VC firm's founding year and its first recorded investment
Early-stage investments	The proportion of a VC firm's total investments allocated to early-stage ventures
Seed stage investments	The proportion of a VC firm's total investments allocated to seed-stage ventures
Prior fundraising flows	The cumulative capital raised by a VC firm before the given observation year
Prior investment rate	The ratio of total capital deployed in investments to the total funds raised before the observation year
Past success rate	The proportion of a VC firm's past investments that resulted in successful exits via IPO or MandA
Gender	The share of female executives within the VC firm

The overconfidence index is built using seven key components. Longer *VC venturing experiences* lead to overconfidence, as firms perceive past success as a result of skill rather than external factors (Linder and Sperber, 2019). Higher *prior fundraising flows* indicate a VC firm's ability to raise large amounts of capital, which results in riskier investment behavior

(Nanda and Rhodes-Kropf, 2013). VC investors who overestimate their ability to pick winners invest aggressively in *seed* and *early-stage* startups. Investing in early-stage startups is riskier and more uncertain and requires high confidence (Chaplinsky and Gupta-Mukherjee, 2016). Likewise, a high *past success rate* reinforces overconfidence, leading to underestimation of risks and aggressive capital deployment (Moy et al., 2024). Additionally, *gender* composition is included in the OC index, as research suggests that male-dominated teams exhibit higher overconfidence in financial decisions (Chen et al., 2019). Overall, the OC Index is designed to capture behavioral traits of VC investors that indicate an overestimation of their abilities, excessive optimism, or risk tolerance.

Each component is assigned a percentile rank. VC firms in the lowest 1% of any component receive a score of 0.01, while those in the top 1% receive a score of 1. OC index is derived by summing the scores across all seven components, resulting in a scale ranging from 0 to 7, where a higher score signifies greater overconfidence. In other words, the overconfidence measure is constructed as a relative, continuous index that varies across VC firms and over time. Hence, the study does not assume that all venture capitalists are overconfident. Lower values reflect more conservative investment behaviour, while higher values capture behavioural patterns that are more consistent with overconfidence. The interpretation is therefore comparative rather than assuming universal overconfidence.

5.2.3 *Econometric model*

The study uses Ordinary Least Square (OLS) regression to evaluate the relationship of the overconfidence VC investor on the post-money valuation of the startup firm. The regression equation is structured as follows:

$$Valuation_n = \alpha + \beta (OC\ index)_i + \delta(syndication)_n + \gamma(firm\ age)_n + \rho(round)_n + v(geographic\ location) + \theta_j + \lambda_t + \epsilon_n \quad (5.1)$$

The study considers the natural log of post-money valuation as the dependent variable, denoted by $Valuation_n$. $OC\ index$ is the overconfidence index of the VC investor i . $syndication$ is the natural log of the total number of investors in a funding round n for the startup. $firm\ age$ is the startup's age at the time of investment during round n . $geographic\ location$ controls for regional effects, acknowledging that investment conditions may vary by location. θ_j denotes industry fixed effects and λ_t denotes year fixed effects. ϵ_n is the error term, capturing unobserved factors affecting the valuation.

This regression framework enables us to isolate the effect of investor overconfidence on startup valuation while accounting for key factors such as syndication and firm characteristics. The inclusion of *syndication* allows us to assess whether the presence of multiple investors has an impact on the startup valuation. *Firm age* serves as a proxy for a firm's maturity and operational experience, both of which are critical factors in assessing risk and growth potential. Firms securing multiple funding rounds are often perceived to be more viable and scalable (Barg et al., 2021). In this study, *Round* is defined as a binary measure based on the sample's median number of funding rounds, which is two. This threshold differentiates firms with median-level funding from those receiving additional investment, indicating greater investor confidence. *Geographic location* identifies whether a startup is situated in a recognised startup hub. This accounts for regional advantages such as access to venture capital and a supportive entrepreneurial ecosystem. In this study, recognised hubs are defined as the top four startup locations in India, namely, Bengaluru, Mumbai, Delhi, and Hyderabad. The measurement of independent variables is provided in Table 5.3.

Table 5.3 Variable description of OC index and other variables

This table provides definitions and measurement details for all variables used in the analysis.

Variable	Description
<i>Firm valuation</i>	Natural log of post-money valuation of the firm in a round
<i>OC index</i>	Overconfidence index of the lead investor in a round
<i>Syndication</i>	Natural log of total number of investors in a round
<i>Firm age</i>	Natural log of difference between funding year and the firm founded year
<i>Round</i>	Binary variable equals 1 if the startup firm had more than two rounds of funding or 0 otherwise
<i>Geographic location</i>	Binary variable equals 1 if the startup firm is located in the startup hub or 0 otherwise

5.3 Results

5.3.1 Summary statistics

Table 5.4 presents the summary statistics. The log-transformed post-money valuation has a mean of 6.85 and a median of 6.65, indicating a relatively balanced distribution. The OC index has an average value of 3.55, ranging from 1.03 to 6.09. The mean value of syndication, measured as the natural logarithm of the total number of investors, is 0.94. The median number of funding rounds in the sample is 2, so the variable *Round* is defined as a binary indicator based on this threshold. Firms with more than two rounds are assigned a value of 1, while others are assigned 0, making this classification a reasonable distinction. Additionally, the mean value for geographic location is 0.64, indicating that a majority of firms are situated in recognized startup hubs.

Table 5.4 Summary statistics – OC index and other variables

This table reports the summary statistics for the key variables, including the mean, standard deviation, minimum, and maximum values. The nature of variables are provided in the bracket.

	mean	median	std dev	min	max
<i>Firm valuation (natural log)</i>	6.85	6.65	1.89	2.28	11.86
<i>OC index</i>	3.55	3.47	1.00	1.03	6.09
<i>Syndication (natural log)</i>	0.94	0.69	0.52	0.69	3.91
<i>Round (binary)</i>	0.42	0.00	0.49	0.00	1.00
<i>Firm age (natural log)</i>	1.57	1.61	0.75	0.00	3.00
<i>Geographic location (binary)</i>	0.64	1.00	0.48	0.00	1.00

Table 5.5 presents the pairwise Pearson correlation coefficients for the key variables used in the analysis. Firm valuation exhibits a positive and significant correlation with the OC index (0.147, $p < 0.05$), firm age (0.522, $p < 0.05$), and investment round (0.496, $p < 0.05$), indicating that older firms and those in later funding rounds tend to have higher valuations. Syndication is negatively correlated with both firm valuation (-0.223, $p < 0.05$) and the OC index (-0.128, $p < 0.05$), suggesting that more syndicated deals are associated with lower valuations and less overconfident investors. Geographic location shows no significant correlation with other variables.

Table 5.5 Correlation matrix

This table presents the pairwise correlation among the key variables to indicate the strength and direction of their linear relationships. Refer Table 5.3 for variable definitions.

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) <i>Firm valuation</i>	1					
(2) <i>OC index</i>	0.147*	1				
(3) <i>Syndication</i>	-0.223*	-0.128*	1			
(4) <i>Firm age</i>	0.522*	0.098*	0.199*	1		
(5) <i>Round</i>	0.496*	0.062	0.136*	0.430*	1	
(6) <i>Geographic location</i>	0.018	0.012	-0.046	-0.025	-0.038	1

5.3.2 Firm valuation and its association with the OC index

To have a preliminary analysis, the sample is divided into two groups based on the firm's average post-money valuation. Group 1 consists of high-value firms, while Group 2 includes

low-value firms. Welch's t-test is used to check if a statistically significant difference exists between each variable for high and low-value firms.

Table 5.6 Mean comparison using Welch's t-test

This table presents the mean differences between groups, tested using Welch's t-test, which accounts for unequal variances between groups. The sample is divided into two groups based on the firm's average post-money valuation.

Variable	Mean	Mean	Difference	t-stat	p-value	Sig.
	Group 1: High-value firms	Group 2: Low-value firms				
<i>OC index</i>	3.717	3.268	0.449	3.826	0.000	***
<i>Syndication</i>	0.778	1.161	-0.384	-5.703	0.000	***
<i>Round</i>	1.688	0.494	1.194	16.389	0.000	***
<i>Firm age</i>	7.822	2.352	5.470	13.286	0.000	***
<i>Geographic location</i>	0.620	0.664	-0.044	-0.732	0.465	

Table 5.6 presents a comparison of key variables between firms with high and low post-money valuations. The OC index is notably higher in firms with a high post-money valuation than firms with a lower valuation. This difference is statistically significant ($p < 0.01$), indicating that startups receiving higher funding are more likely to have investors exhibiting stronger overconfidence. This finding suggests a potential link between investor overconfidence and inflated startup valuations.

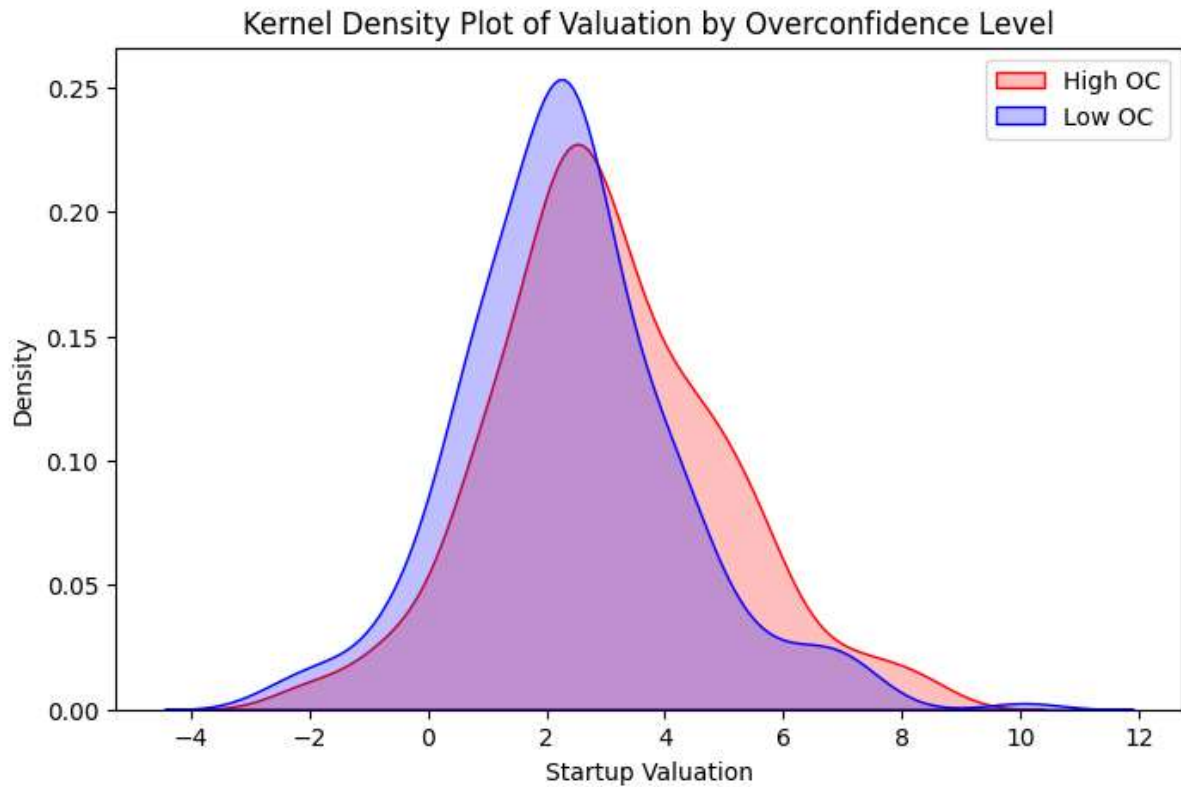
Firms with higher post-money valuations also tend to have fewer investors in syndicates. The mean syndication is 0.78 for high-value firms compared to 1.16 for low-value firms. This negative and statistically significant difference ($p < 0.01$) suggests that highly valued firms are associated with fewer co-investors. On average, high post-money valuation firms have undergone more previous funding rounds than lower-valued firms ($p < 0.01$). Firm age also plays a crucial role, as high-value firms have an average age of 7.82 years, and low-value firms

have 2.35 years, and the difference of 5.47 years is statistically significant ($p < 0.01$). However, the geographic location of the startup firm does not appear to be a significant determinant of startup valuation, as no meaningful statistical difference was observed ($p = 0.46$).

Figure 5.1 illustrates the distribution of startup valuations for high overconfidence (high OC) and low overconfidence (low OC) groups using a Kernel Density Plot. The low OC (blue) curve peaks slightly to the left of the high OC (red) curve, indicating that startups with lower overconfidence generally have lower valuations. The density curve for low OC investors exhibits a higher peak, indicating that their valuations are more concentrated around a central value with lower variability. This suggests that less overconfident investors adopt a more conservative approach rather than aggressive forecasting. The wider spread and longer right tail of the high OC curve suggest greater variability in valuations, with some startups achieving significantly higher valuations. These findings also support the notion that the overconfidence of investors drives startup valuation. The study sets to further explore the nuances of this relationship using regression analysis in the following section.

Figure 5.1 Kernel density plot of distribution of startup valuation for high and low OC index

This figure shows the kernel density plot of startup valuations for groups with high and low overconfidence (OC) index scores. The plot illustrates how valuations are distributed within each group. The height of each curve at a given point on the x-axis indicates the relative concentration of observations at that valuation level, allowing visual comparison of how startup valuations differ between high and low OC investors.



While kernel density plots are used to visually compare valuation distributions across investor types, a formal two-sample Kolmogorov-Smirnov (K-S) test is additionally conducted to statistically assess whether these distributions differ. The K-S test compares the entire distribution rather than focusing on mean differences, making it well suited to validate the visual patterns observed in the density plots. The test rejects the null hypothesis of identical valuation distributions between startups backed by high- and low-overconfidence investors ($D = 0.249$, $p = 0.003$). This result formally confirms that the visual differences observed in the kernel density plots reflect statistically significant distributional differences. As this analysis is descriptive, the findings are interpreted as evidence of association rather than causality.

5.3.3 VC overconfidence, syndication and startup valuation

Table 5.7 presents the empirical results evaluating the impact of overconfidence on startup valuation. Model (1) shows that the OC index has a positive significant impact on startup

valuation. Model (2) controls for heterogeneity using industry and year dummies, and the results remain consistent. Across all models, the OC index has a positive and significant effect on firm valuation. This supports the hypothesis that overconfident VCs tend to overestimate startup valuation.

Table 5.7 Overconfidence, syndication and firm valuation

This table reports the results examining the relationships among investor overconfidence, syndication, and startup valuation. Variable definitions are provided in Table 5.3. Fixed effects (FE) are included as listed in the model specification.

Variables	(1)	(2)	(3)
<i>OC index</i>	0.155* (0.088)	0.147* (0.085)	0.399*** (0.152)
<i>OC*Syndication</i>			-0.281** (0.128)
<i>Syndication</i>	-0.365*** (0.123)	-0.310*** (0.116)	0.591 (0.408)
<i>Round</i>	1.270*** (0.165)	1.156*** (0.158)	1.169*** (0.159)
<i>Firm age</i>	0.911*** (0.116)	0.923*** (0.121)	0.917*** (0.120)
<i>Geographic location</i>	-0.009 (0.166)	0.050 (0.161)	0.070 (0.162)
Constant	0.514 (0.441)	0.485 (0.404)	-0.344 (0.557)
Industry	NO	YES	YES
Year	NO	YES	YES
Observations	509	509	509
R^2	0.380	0.456	0.460
$Adj. R^2$	0.374	0.413	0.416

The study then follows to explore the moderating role of syndication. Prior research suggests that syndication also facilitates information pooling, peer monitoring, and collective screening among venture capitalists (Gompers et al., 2001; Tian, 2012). Through the involvement of

multiple investors, investment decisions are subjected to diverse perspectives, expertise, and due diligence processes. These mechanisms can mitigate the influence of individual-level behavioural biases, including overconfidence, by introducing greater scrutiny and coordination in decision-making. Accordingly, in this study, the moderating effect of syndication is interpreted as arising from these broader informational and governance functions, rather than solely from risk-sharing considerations.

In Table 5.7, Model (3), the coefficient of the interaction term ($OC*Syndication$) is negative and significant, indicating a dampening effect. This confirms that as investor syndication increases, OC's effect on valuation decreases, supporting the moderating hypothesis. When multiple investors are involved (higher syndication), they act as a check on overconfident valuations, leading to more balanced investment decisions. The results also show that investor syndication alone has mixed effects. In models (1) and (2), syndication has a negative and significant effect on valuation. This suggests that syndicated deals tend to have lower valuations, due to thorough due diligence and risk assessment by multiple investors. However, in Model (3), syndication loses significance. This implies that once the moderating effect is included, syndication alone does not drive valuation directly. Instead, its role is mainly in adjusting the effect of overconfidence on valuation. These findings reinforce the idea that overconfident VCs are more likely to inflate valuations, while checks and balances provided by multiple investors help minimize the overvaluation risk linked to overconfident investors.

Round and *Firm age* consistently show positive and significant effects across all models, implying that firms in later funding rounds and those that are older receive higher valuations. However, as suggested by earlier results, the prominence of being located in a startup hub does not significantly impact the valuation of the startup. The inclusion of industry and year dummies in Models 2 and 3 enhances the explanatory power of the models, indicating an improved model fit.

In summary, the findings reinstate that the overconfidence of VC investors plays a crucial role in shaping startup valuations. The significantly higher OC index in firms with high post-money valuations aligns with behavioral finance theories, which suggest that overconfident investors overestimate a startup's potential and drive up its valuation. The study also find that highly valued firms have fewer co-investors, suggesting that lead investors in these deals have greater confidence in their investment choices. Successfully raising multiple rounds suggests strong market validation, reduced investment risk, and positive investor sentiment, which can contribute to higher valuations in subsequent rounds. The result also shows that firms that have successfully raised multiple rounds in the past tend to secure higher valuations in subsequent funding rounds. Similarly, firm age is positively associated with post-money valuation, suggesting that more mature startups have had time to build credibility, develop their business models, and achieve higher firm value. Interestingly, geographic location does not appear to influence valuation outcomes, as no statistically significant difference was observed. This implies that in the given dataset, location-specific advantages, such as being situated in a startup hub, do not always lead to higher valuations.

5.4 Summary of findings and implications

This study examines the impact of VC investors' overconfidence on firm valuation, highlighting how overconfident investors tend to overestimate their ability to identify high-growth startups, leading to inflated valuations. However, investor syndication serves as a corrective mechanism, minimizing the influence of overconfidence through collective assessment.

These findings have both theoretical and practical implications for venture capital investment and startup valuation. Theoretically, the study extends behavioral finance literature by

demonstrating how cognitive biases, particularly overconfidence, influence investment decisions, leading to inflated startup valuations. It also contributes to syndication research by showing that collective decision-making moderates the impact of overconfidence. Practically, the results highlight the importance of investor syndication in minimizing valuation distortions, suggesting that startups seeking funding and VC firms structuring deals should prioritize diverse investor participation to enhance due diligence and reduce bias-driven mispricing.

The study faces inherent data limitations, particularly the difficulty in identifying lead investors. Expanding data availability could strengthen future research by incorporating additional variables and exploring how they vary for cross-border investments. Further studies could also examine how syndication dynamics evolve across different investment stages and market conditions, offering deeper insights into the mechanisms that shape startup valuation.

This study contributes to the literature on investor overconfidence and venture capital decision-making in various ways. Prior research has established that overconfident investors overestimate their knowledge and ability to interpret information, which in turn contributes to mispricing and overvaluation (Brown and Cliff, 2005; Trejos et al., 2019). While overconfidence has been studied in corporate finance and mutual fund management (Adebambo and Yan, 2016; Bailey et al., 2011; Puetz and Ruenzi, 2011), its implications in the VC context have not been explored much. The contemporary literature in the VC landscape reports the relationship between the overconfidence of investors and their entrepreneurial selection (Robinson and Marino, 2015; Zacharakis and Meyer, 2000; Zacharakis and Shepherd, 2001) and fundraising decisions (Ben Amor and Kooli, 2024; Kafeshani et al., 2018; Moy et al., 2024). This study extends the literature by investigating how overconfidence among VC investors influences startup valuation, an area that remains underexplored. Additionally, the study examines syndication (Brander et al., 2002; Manigart et al., 2006), a defining feature of VC investments, and assesses its role as a moderating mechanism in minimizing the valuation

distortions caused by overconfidence. Finally, by focusing on India, which has evolved as a hub for budding entrepreneurs, this study contributes to the emerging market literature.

Chapter 6

Drivers of venture capital funding

6.1 Research Overview

Over the past three decades, venture capital has emerged as a pivotal source of external finance for startups navigating uncertain markets and rapid growth trajectories. The decision to invest in a new venture is inherently risky and complex, often shaped by a mix of signals about the startup's potential to generate future returns. Chapters 3 and 4 of this thesis have demonstrated that financial indicators such as liquidity, profitability, and solvency ratios play a significant role in determining a startup's valuation. However, whether these same financial indicators are actively considered by venture capitalists when deciding how much funding to provide remains an open empirical question. This chapter seeks to address this gap by examining whether the factors that drive startup valuation align with the signals that investors prioritize when making funding decisions.

The role of financial indicators in shaping funding outcomes is particularly relevant because VC funding has implications far beyond the initial capital injection. Funding decisions influence how startups structure operations, pursue growth opportunities, and compete in their respective markets. They can also affect the firm's long-term survival, exit potential, and profitability (Islam et al., 2018). Despite their importance, it is still unclear whether investors systematically factor in objective measures of financial health due to information asymmetry (Ekholm, 2006).

This chapter first focuses on founder-level characteristics that may signal capability and credibility to potential investors. Attributes such as prior entrepreneurial experience, industry

expertise, and educational background are commonly cited in the entrepreneurial finance literature as signals of lower information asymmetry and higher likelihood of venture success. Next, the analysis investigates the role of firm-level financial variables to assess whether investors consider these quantitative indicators when determining funding amounts.

Recognizing that funding decisions do not occur in isolation, this study also controls for broader macroeconomic factors that may influence investor sentiment and capital availability. By doing so, it aims to disentangle firm- and founder-specific effects from external conditions that could drive funding trends.

Methodologically, this chapter adopts a mixed-methods approach to provide robust evidence. A multi-layer perceptron (MLP) neural network model is used to uncover complex, non-linear patterns in the data that traditional regression methods may overlook. The objective is to gather a more comprehensive understanding of whether venture capitalists align their funding decisions with the financial fundamentals that underlie a startup's valuation and what additional signals weigh heavily in their assessments.

6.2 Data and Methodology

6.2.1 Sample Data

The study utilises data on Indian startups founded between 2000 and 2020. These firms have secured VC funding from Seed to Series J, generated revenue from operations, facilitated exits for investors through mergers and acquisitions (M&A) or initial public offerings (IPOs), and maintained an active status (not categorised as Deadpool). After considering all these filters, the final sample includes 552 Indian startups with 1,219 funding rounds. This sample also ensures the availability of key founder, financial, and investment-level variables. The data

source is Tracxn, a leading startup intelligence platform. The distribution of sample across the industries and years are given in Table 6.1.

Table 6.1 Sample distribution

This table represents the distribution of sample firms. Panel A reports the industry-wise distribution of the sample firms, Panel B shows the distribution by founding period, and Panel C presents the funding round-based sample distribution. The total sample includes 552 firms across different sectors and founding years.

Panel A: Industry-wise sample distribution

Industry	Number of firms
Ed Tech	31
Financial Services	103
Health & services	55
IT & Services	55
Retail	90
Others	218
Total	552

Panel B: Year-wise sample distribution

Year	Number of firms
2000-2005	35
2006-2010	113
2011-2015	234
2016-2020	170
Total	552

Panel C: Funding round-wise distribution

Round name	Number of funding rounds
Seed	438
Series A	360
Series B	194
Series C	115
Series D+	112
Total	1219

6.2.2 *Variable description*

In this study, we deliberately include actual financial variables, such as total revenue, cash balances, or total assets, alongside or instead of purely ratio-based indicators. While financial ratios are valuable for summarizing relative performance and efficiency, they can sometimes mask important scale effects or introduce statistical noise, especially in early-stage startups where denominators like fixed assets or equity can be very small and volatile. Using actual values allows us to capture the real size, liquidity, and financial muscle of a startup factors that can directly influence a venture capitalist's funding decision. For example, a startup's absolute cash reserves or total revenue may signal its capacity to sustain operations or expand quickly, which ratios alone may not fully reflect. By combining actual variables with other founder and macroeconomic controls, our approach aims to provide a more complete and realistic view of the signals that investors observe when evaluating funding amounts. The natural logarithm of the *funding amount* of each round is the dependent variable in the first part of the study. A detailed description of all the variables is provided in Table 6.2.

The study uses a two-digit National Industry Code (NIC) for the industry classification of Indian firms. Two-digit classification provides broader industry categories, ensuring an adequate number of observations for meaningful analysis (Nguyen and Vo, 2021)

Table 6.2 Variable description of VC funding drivers

Variable	Description
<i>Dependent variables:</i>	
<i>VC funding</i>	Natural log of total funding amount invested by the VC in a startup in the given round
<i>Financial variables:</i>	
<i>Revenue from operations</i>	Natural log of revenue from operations of the firm for the year prior to the funding year
<i>EBIT margin</i>	The ratio of Earnings before interest and taxes (EBIT) to revenue from operations
<i>Operating expense</i>	Natural log of operating expenses of the firm for the year prior to the funding year
<i>Finance cost</i>	Natural log of finance cost of the firm for the year prior to the funding year
<i>Fixed assets</i>	Natural log of value of fixed assets held by the firm in the year prior to the funding year
<i>Long-term debt</i>	Natural log of value of long-term debt of the firm prior to the funding year
<i>Paid-up share capital</i>	Natural log of paid-up share capital of the firm prior to the funding year
<i>Cash and bank balance</i>	Natural log of total cash and bank balances of the firm for the year prior to the funding year
<i>Founder characteristics:</i>	
<i>Entrepreneurial experience</i>	Natural log of the number of prior startups founded by the team, plus one
<i>Managerial Experience</i>	Binary variable, taking the value '1' if the founding team has prior managerial experience, '0' otherwise
<i>Premier institute education</i>	Binary variable, taking the value '1' if founders graduated from a premier educational institution ^a , '0' otherwise
<i>Geographic location</i>	Binary variable, taking the value '1' if the firm is located in a recognized startup hub ^b , '0' otherwise
<i>Female founders</i>	Natural log of the number of female co-founders in the team, plus one
<i>Macro-economic factors:</i>	
<i>Annual VC investment</i>	Natural log of total VC investment in the country each year
<i>Stock market capitalization</i>	Stock market capitalization to GDP percentage for the year
<i>Controls:</i>	
<i>Firm age</i>	Natural log of the difference between the funding year and startup founded year, plus one
<i>Investor syndication</i>	Natural log of the total number of investors who participated in the current funding round, plus one
<i>Institutional investor</i>	Binary variable, taking the value '1' if institutional investors participated in previous funding rounds, '0' otherwise

Note: a) For the purpose of this study, premier educational institutions are defined as IITs, IIMs, IISc, IISERs, and AIIMS in India

b) Recognised hubs are defined as the top four startup locations - Bengaluru, Mumbai, Delhi, and Hyderabad

6.2.3 Analytical model

6.2.3.1 Regression Specification and Estimation Method

To investigate the factors that influence startup valuation and venture capital funding amounts, this study employs an Ordinary Least Squares (OLS) regression framework with high-dimensional fixed effects. The models are estimated using the `reghdfe` command in Stata (Correia et al., 2020), which extends standard fixed effects regression by efficiently absorbing multiple levels of fixed effects, such as firm, industry, and time, while correcting for potential within-group correlation. This approach controls for unobserved heterogeneity that could otherwise bias the results and provides cluster-robust standard errors to address potential heteroskedasticity and autocorrelation, ensuring that the coefficient estimates and significance levels remain reliable.

To address potential selection bias in the funding decision, the Heckman sample selection model, as detailed in Chapter 3, Equation 3.4, is applied. In the second stage, to analyse the factors driving the funding amount, the following regression is used

$$Y_{j,s} = \alpha + \beta (\text{financial indicators})_{j,s} + \delta (\text{founder characteristics})_{j,s} + \rho(\text{macroeconomic indicators})_t + \sum_k \gamma_k (\text{controls})_{j,s} + imr + \epsilon_{j,s} \quad (6.1)$$

The natural log of the VC funding amount received by startup firm j at stage s , denoted by $Y_{j,s}$. $\text{financial indicators}_{j,s}$ is a vector of the performance indicators of the startup firm derived from the financial statements, $\text{founder characteristics}_{j,s}$ is a vector of the founder team attributes and $\rho(\text{macroeconomic indicators})_t$ represents the macroeconomic conditions in which the startup firm operates during the year t . imr indicates the inverse Mills ratio.

Table 6.3 provides the expected signs of the coefficients for the independent and control variables, as derived from the literature.

Table 6.3 . Hypothesized relationships from literature

Variable	Expected sign
<i>Financial indicators</i>	
<i>Revenue from operations</i>	+
<i>EBIT margin</i>	+
<i>Operating expense</i>	-
<i>Finance cost</i>	-
<i>Fixed assets</i>	+
<i>Long-term debt</i>	-
<i>Paid-up share capital</i>	+
<i>Cash and bank balance</i>	+
<i>Founder characteristics</i>	
<i>Entrepreneurial experience</i>	+
<i>Managerial Experience</i>	+
<i>Premier institute education</i>	+
<i>Geographic location</i>	+
<i>Female founders</i>	-
<i>Macro-economic factors:</i>	
<i>Annual VC investment</i>	+
<i>Stock market capitalisation</i>	+
<i>Deal characteristics</i>	
<i>Firm age</i>	+
<i>Investor syndication</i>	-
<i>Institutional investor</i>	+

6.2.3.2 Multi-Layer Perceptron (MLP) neural network

The funding process for new ventures involves multiple steps, and the contextual drivers of funding and their impact may vary over stages, across industries, and within different economic conditions (Berre and Le Pendeven, 2023). Hence, this study explores the possibility of employing a data-driven neural network model to let the data decide the underlying relationship between the

variables. Consequently, we utilise the MLP neural network model in this analysis. Neural network models often outperform traditional statistical models in terms of predictive accuracy (Tashakkori et al., 2024), which is critical for providing actionable insights to investors and startups. They capture complex non-linear relationships between variables (Ravi and Pramodh, 2010), which is essential when modelling the intricate dynamics of startup funding influenced by various factors. MLPs are also capable of handling noise and variability in the data, making them suitable for real-world datasets that may contain outliers or unstructured data.

6.3 Results

6.3.1 Summary statistics

Table 6.4 presents the summary statistics for the variables used to analyze startup valuation and funding dynamics. The sample includes 1,219 firm-year observations of VC-funded Indian startups. On average, these firms report moderate revenue from operations, with considerable variation reflected in the standard deviation. Similarly, operating expenses and finance costs also show significant spread, indicating diverse cost structures and funding strategies among the sample firms. Variables capturing founder and investor characteristics, such as entrepreneurial experience, managerial experience, and institutional investor presence, highlight notable heterogeneity. The presence of syndication and institutional investors suggests a substantial share of startups benefit from diversified investor participation.

Table 6.4 Summary statistics of VC funding drivers

This table reports summary statistics for the key variables used in the analysis. Variable descriptions are provided in Table 6.2.

Variable	Obs	Mean	SD
<i>VC funding</i>	1219	0.722	2.061
<i>Revenue from operations</i>	1219	4.658	2.743
<i>EBIT Margin</i>	1219	-4.935	9.683
<i>Operating expense</i>	1219	5.638	2.108
<i>Finance cost</i>	1219	0.981	2.851
<i>Fixed assets</i>	1219	2.535	1.809
<i>Long-term debt</i>	1219	3.315	2.112
<i>Equity share capital</i>	1219	3.821	2.202
<i>Cash and equivalents</i>	1219	2.111	2.008
<i>Investor syndication</i>	1219	1.540	0.803
<i>Institutional investor</i>	1219	0.856	0.352
<i>Entrepreneurial experience</i>	1219	0.243	0.414
<i>Managerial experience</i>	1219	0.989	0.107
<i>Premier institute education</i>	1219	0.501	0.500
<i>Female founders</i>	1219	0.206	0.354
<i>Geographic location</i>	1219	0.651	0.477
<i>Firm age</i>	1219	1.538	0.731
<i>Annual VC investment</i>	1219	13.928	1.081
<i>Stock Market Capitalization</i>	1219	4.343	2.341

6.3.2 *Drivers of later-stage VC funding*

Table 6.5 presents the results of influence of founder characteristics on VC funding amount received by the startup firm. Across both model specifications, founder education from a premier institution consistently shows a strong and statistically significant positive effect on the likelihood of securing VC funding. This highlights the signaling power of elite education in high-uncertainty investment contexts (Colombo and Grilli, 2005; Hsu, 2007).

Entrepreneurial experience also shows a positive association, suggesting that prior entrepreneurial exposure modestly enhances founder credibility in the eyes of investors (Zott and Huy, 2007). In contrast, managerial experience, geographical location, and the presence of female co-founders do not exhibit significant effects, indicating that these factors may carry less weight in funding decisions once other signals are accounted for.

Among the control variables, stock market capitalization, a proxy for broader market conditions, has a small but significant positive effect, implying that favorable capital market environments can indirectly boost VC flows into startups. Firm age is strongly significant, demonstrating that older firms are more likely to attract VC funding, reflecting accumulated credibility or reduced information asymmetry over time (Kalyanasundaram et al., 2021). Interestingly, investor syndication shows a negative effect, significant in the second model, which may suggest that more complex syndication structures could dilute individual investors' incentives or signal higher perceived risk. The presence of an institutional investor has a large, positive, and robust association with VC funding, underlining the critical role that credible institutional backers play in attracting further capital. Finally, the inverse Mills ratio (IMR) is positive and significant, confirming the importance of correcting for potential selection bias in the sample.

Table 6.5 VC funding and founder characteristics of startup firm

This table presents the results OLS regression, with the dependent variable being the natural logarithm of the VC funding amount and the independent variables being founder characteristics. Standard errors are included in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Refer to Table 6.2 for the variable definitions.

	(1) VC funding	(2) VC funding
<i>Entrepreneurial experience</i>	0.011* (0.125)	0.091* (0.126)
<i>Managerial experience</i>	0.089 (0.470)	0.053 (0.476)
<i>Premier institute education</i>	0.285*** (0.108)	0.316*** (0.108)
<i>Geographical location</i>	-0.070 (0.112)	-0.013 (0.112)
<i>Female co-founders</i>	-0.155 (0.156)	-0.086 (0.151)
<i>Annual VC investment</i>	0.104 (0.135)	0.064 (0.137)
<i>Stock market capitalization</i>	0.017** (0.008)	0.022*** (0.008)
<i>Firm age</i>	0.820*** (0.087)	0.712*** (0.086)
<i>Investor syndication</i>	-0.098 (0.077)	-0.157** (0.078)
<i>Institutional investor</i>	0.867*** (0.239)	0.909*** (0.241)
<i>imr</i>	2.566*** (0.498)	3.026*** (0.500)
Constant	-1.101 (1.652)	-0.200 (1.664)
Industry FE	Yes	No
Stage FE	No	Yes
N	1219	1219
R^2	0.270	0.191
$Adj. R^2$	0.245	0.182

Table 6.6 VC funding and financial indicators of startup firm

This table presents the results of OLS regression, with the dependent variable being the natural logarithm of the round funding amount. Standard errors are included in brackets. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. Refer to Table 6.2 for the variable definitions.

	(1) VC Funding	(2) VC Funding	(3) VC Funding
<i>Revenue from operations</i>	0.308*** (0.034)	0.211*** (0.031)	
<i>EBIT Margin</i>			0.001 (0.001)
<i>Operating expenses</i>			-0.605*** (0.037)
<i>Finance cost</i>			-0.025* (0.020)
<i>Fixed assets</i>	0.050 (0.042)		
<i>Long-term debt</i>		0.101*** (0.026)	
<i>Paid-up share capital</i>		0.225*** (0.030)	
<i>Cash and bank balances</i>	0.021 (0.032)		
<i>Annual VC investment</i>	0.229* (0.132)	0.194 (0.121)	0.122 (0.128)
<i>Stock market capitalization</i>	0.005 (0.007)	0.003 (0.007)	0.001 (0.007)
<i>Firm age</i>	0.536*** (0.181)	0.541*** (0.181)	0.538*** (0.181)
<i>Investor syndication</i>	0.055 (0.075)	0.050 (0.073)	0.140** (0.071)
<i>Institutional investor</i>	1.604*** (0.148)	1.510*** (0.142)	1.442*** (0.136)
<i>imr</i>	1.671*** (0.476)	1.536*** (0.480)	0.650 (0.463)
Constant	4.173** (1.755)	4.142** (1.639)	5.094** (1.666)
Industry	Yes	Yes	Yes
N	1219	1219	1219
R ²	0.503	0.542	0.595

Table 6.6 examines the influence of financial variables on VC funding. In Model (3), EBIT margin (calculated as EBIT divided by revenue from operations) is included as a proxy for earnings to mitigate potential multicollinearity. Furthermore, because operating expenses and revenue are highly correlated, they are introduced in separate model specifications to avoid distortions in the estimates.

All the results reported in Table 6.6 confirm that VC investors value financial indicators to make their investment decisions. Revenue from operations has a positive and significant impact across all the models, which reflects a firm's ability to expand and position itself competitively. Operating expenses and finance costs have a significant negative impact, meaning VCs are cautious about startups with a higher degree of operating and financial leverage. This implies that inefficient cost structures or high debt servicing costs deter VC investments. Paid-up share capital is found to be positive and significant in driving funding in both countries, highlighting that VCs favour startups that have stronger initial financial backing and view paid-up capital as a sign of long-term viability and lower financial risk.

The results also identify that long-term debt is positively significant for Indian startup funding. The positive coefficient of long-term debt aligns with existing literature, which suggests that startups with well-managed debt are more likely to experience higher revenue and improve survival rates (Cole and Sokolyk, 2018; Epure and Guasch, 2020). This infers that startups benefit from accessing external debt to finance operations or growth, highlighting the importance of lower-cost debt financing.

In addition to these factors, investor syndication, where multiple investors collaborate on a funding round, emerges as another significant factor influencing VC funding in both markets. This finding suggests that the pooling of resources and sharing risk between investors are vital components in driving funding decisions. Syndicated investments not only mitigate individual investor risk but also bring in diverse expertise, which can be instrumental in the growth and success of a startup.

The presence of institutional investors in previous funding rounds appears to have a particularly strong impact on VC funding decisions. This indicates that the presence of institutional investors enhances the credibility of the startup firm seeking funding.

In this study, the issue of potential reverse causality between startup financial performance and the amount of VC funding received is an important methodological concern. Ideally, a Granger causality test would be applied to determine whether past financial performance predicts future funding (and vice versa). However, this method requires consistent, continuous time series data with evenly spaced observations, which is not feasible in the context of startup funding. Funding rounds occur at irregular intervals that vary across firms, and financial information such as revenue is typically available only for the preceding fiscal year, resulting in gaps and inconsistencies in the time dimension.

Given these constraints, this research instead uses lagged financial variables as predictors of funding amount. This approach ensures that the financial indicators temporally precede the funding event, thereby addressing the possibility of reverse causality to some extent. Nonetheless, this method cannot fully rule out endogeneity, as unobserved factors (such as founder capabilities or market conditions) may simultaneously influence both financial performance and investors' funding decisions. Therefore, the results should be interpreted as robust associations, with appropriate caution.

To complement these regression results and further explore potential non-linear and complex relationships among the variables, this study also employs a Multi-Layer Perceptron (MLP) analysis. The MLP provides an alternative, data-driven perspective that does not rely on strict parametric assumptions and can capture hidden patterns that traditional linear models might overlook. This additional layer of analysis helps to test the robustness of the findings and offers deeper insights into how founder characteristics, financial health, and contextual factors interact to shape funding outcomes.”

Table 6.7 VC funding determinants using MLP model

This table presents the variable importance of funding determinants of Indian startups using the Multi-Layer Perceptron Neural network. The dependent variable is the natural logarithm of the investment amount for each round, and the independent variables definition is provided in Table 6.2.

Variables	Variable importance
<i>Business performance indicators</i>	
<i>Revenue from operations</i>	0.080
<i>EBIT margin</i>	0.075
<i>Operating expense</i>	0.275
<i>Finance cost</i>	0.026
<i>Fixed assets</i>	0.032
<i>Long-term debt</i>	0.043
<i>Paid-up share capital</i>	0.056
<i>Cash and bank balance</i>	0.028
Subtotal	0.615
<i>Founder characteristics</i>	
<i>Entrepreneurial experience</i>	0.026
<i>Premier institute education</i>	0.045
<i>Managerial Experience</i>	0.011
<i>Geographic location</i>	0.009
<i>Female founders</i>	0.023
Subtotal	0.115
<i>Macro-economic factors</i>	
<i>Annual VC investment</i>	0.035
<i>Stock market capitalization</i>	0.018
Subtotal	0.053
<i>Controls</i>	
<i>Firm age</i>	0.052
<i>Investor syndication</i>	0.067
<i>Institutional investor</i>	0.098
Subtotal	0.217

The findings from Table 6.7 reinforce the earlier findings by providing empirical, data-driven validation of the VC investment approaches in India. The use of an MLP model adds credibility to the results by ensuring that variable importance is determined based on actual predictive contributions rather than simple correlations.

The variable importance indicated by the MLP model refers to the relative contribution or influence of each input feature in predicting the target variable. The target variable is the VC

funding received by the startup firms. Among all predictors, business performance indicators emerge as the most influential, accounting for approximately 61.5% of the total variable importance. Within this group, operating expenses stand out with the highest individual importance (0.275), followed by revenue from operations and EBIT margin, underscoring the critical role of core financial health in securing funding. Founder characteristics contribute a smaller but still notable share (11.5%), with premier institute education and entrepreneurial experience emerging as the most relevant signals within this category.

Macro-economic factors, such as annual VC investment levels and stock market capitalization, have relatively lower importance (5.3%), suggesting that firm-specific and founder-specific factors weigh more heavily than broader market conditions in the model's predictions.

Control variables, including firm age, investor syndication, and the presence of institutional investors, together account for about 21.7% of the total, highlighting their non-trivial role in shaping funding prospects. Overall, the MLP results align with the regression findings, reinforcing the dominant role of financial fundamentals while also capturing the continued relevance of credible founder signals and deal-specific factors.

The methodological strength of the MLP model enhances the reliability of our findings by offering a non-parametric, data-driven approach, and the numerical importance scores provide granular quantification of each factor's influence. The consistency between machine learning results and prior conceptual insights increases confidence in the validity of these findings, confirming that VC funding is primarily financial-performance-driven. The model has a training error of 0.352 and a testing error of 0.486, indicating a reasonably balanced fit.

6.4 Summary of the findings

This analysis sheds light on whether the factors driving VC funding and startup valuation align or diverge. On the one hand, the evidence shows that firm-level financial variables such as profitability, liquidity, and cost structures consistently play a significant role in both contexts. This suggests that robust financial health and operational discipline are fundamental signals that matter to investors not only when determining how much capital to commit but also in assessing a startup's market worth.

However, when examining founder characteristics, a subtle but important distinction emerges. Signals such as premier institute education appear to have a stronger influence on securing funding than on directly driving valuation levels. This suggests that investors often rely on subjective or 'soft' signals such as elite educational backgrounds to gauge the credibility and potential of founding teams. However, this reliance can be tricky, as such credentials do not necessarily translate into tangible business performance or higher valuation outcomes.

It is important to note that the results presented in this chapter are based on startups that survive long enough to raise multiple funding rounds and disclose valuation information. Firms that fail early or exit the funding market prior to observation are therefore underrepresented, introducing potential survivorship bias. Although the Heckman correction accounts for selection into observed funding rounds among surviving firms, the findings should be interpreted as conditional on continued survival and investor engagement. This limitation is inherent to venture financing data and is common in empirical studies of startup valuation.

Moreover, this study is subject to certain limitations due to data constraints. While the empirical analysis relies on a parsimonious model that prioritises key variables to enhance clarity and interpretability, it does not capture the full complexity of all factors that may influence VC funding decisions. Nonetheless, this approach offers valuable insights into the

primary drivers of investment behaviour and provides a structured framework for understanding the dynamics of startup financing.

Chapter 7

Summary and Conclusion

This chapter summarises the key research findings and highlights the contributions to both theory and practice in entrepreneurial finance. This thesis extends the long-lasting debate about the influence of *jockey* (the founder) or the *horse* (firm performance) on startup success by introducing the *Jockey-Horse-Meadows-Trainer* framework, which integrates the industry attractiveness (*the meadows*), and investor behavior (*the trainer*) into the valuation dynamics.

Drawing on a dataset of Indian startups founded between 2000 and 2020 and funded by venture capital investors, this study primarily explored the impact of founder characteristics and financial indicators in shaping the growth of startup valuations to provide new empirical evidence on *jockey-horse* framework in emerging market context. To add on the influence of *meadows*, the impact of industry attractiveness on firm valuation has been explored. To validate the role of *trainer*, the study evaluates the impact of VC investor overconfidence on startup valuations. Finally, to draw parallels between what drives startups' valuation success and what VC investors perceive as crucial determinants while funding, the study investigates the firm-level and macro-level factors that determine VC funding.

Section 7.1 provides a detailed summary of the empirical results. Sections 7.2 and 7.3 discuss the contributions and practical implications, respectively. Section 7.4 outlines the study's limitations and suggests directions for future research. Finally, Section 7.5 gives an overall conclusion of the thesis.

7.1 Summary of the main results

At the heart of this research is the recognition that startup trajectories are not static milestones but are stories shaped by multiple, interacting forces. This study challenges the traditional, binary notions of entrepreneurial success by framing startup outcomes as dynamic and continuous rather than static yes-or-no milestones like funding or exit. By modeling success as the probability of securing higher valuations across funding rounds, it captures the fluid reality of how startups grow, stall, or pivot over time. This perspective enables a more nuanced understanding of value creation as an unfolding process rather than a single event.

A central finding of the research is the evolving role of firm-level financial performance as startups mature. Early-stage investors weigh founder pedigree and narrative more heavily, but as ventures progress through funding rounds, financial performance of the firm gains critical significance. While this general pattern is well recognised in theory, this study provides clear empirical evidence pinpointing exactly which financial indicators gain prominence over time, offering a more detailed understanding of how investor priorities shift as ventures mature. Measurable indicators such as leverage, liquidity, and operational efficiency becomes critical drivers of valuation growth. Interestingly, higher debt-to-equity ratio is positively associated with valuation growth, suggesting that prudent use of debt financing enhances startups' capacity to scale. The results indicate a shift that underlines the increasing importance of financial discipline and sound operations in sustaining investor confidence and driving valuations upward as startup moves ahead in its life cycle.

In addition to founder and firm-level factors, the study reconceptualizes how industry conditions influence startup valuation. Contrary to the linear assumption that more attractive industries uniformly boost valuations, the results uncover a non-linear, reverse S-shaped

pattern. Furthermore, the analysis finds that industry-level and firm-level signals function as substitutes rather than simple complements. When credible firm-level performance data are available, investors rely less on broad industry signals, demonstrating selective attention to the most salient information under constrained decision-making conditions.

The study further expands the conversation by bringing behavioural finance into the startup valuation space. Investor overconfidence is operationalized as a behavioural proxy that aggregates multiple cognitive mechanisms, including biased self-assessment, overestimation of private information, and underweighting of downside risk. Interpreted in this light, the positive association between overconfidence and valuation reflects a tendency for prices to deviate from fundamentals in high-uncertainty settings. Importantly, the mitigating role of syndication suggests that collective investment structures partially discipline these behavioural biases through shared due diligence and risk pooling. Together, these findings highlight how behavioural tendencies and institutional mechanisms jointly shape valuation outcomes in environments characterized by information asymmetry.

In addition to explaining how startups achieve higher valuations, the study also sheds light on the broader drivers of funding access itself. This analysis highlights whether the factors behind VC funding and startup valuation are consistent. Financial indicators such as profitability, liquidity, and cost structures play an equally important role in both contexts, showing that strong financial discipline is central to securing investment and driving valuation. However, founder-related signals reveal a subtle difference. Traits like education from premier institutions tend to have a stronger influence on attracting funding than on directly shaping valuation levels. This suggests that reliance on softer credentials have to be approached with caution, as such signals may not always align with the measurable performance needed to create long-term value.

To integrate these diverse insights, the study adopts an extended *horse–jockey–trainer–meadow* framework, enriching the traditional *horse–jockey* analogy by factoring in the roles of industry context (*meadows*) and investors (*trainers*). This framework bridges theoretical and practical perspectives, offering a holistic yet accessible way for entrepreneurs, venture capitalists, policymakers, and advisors to grasp the layered realities of startup valuation in complex, uncertain, and evolving environments.

7.2 Contributions of the study

This study makes several key contributions to the literature on entrepreneurial finance, startup valuation, and decision-making under uncertainty, particularly within the context of emerging markets.

(i) Redefining entrepreneurial success

Traditional studies often rely on binary outcomes such as funding, exit, or survival to measure startup success. This study advances the discourse by modeling success as a continuous probability of achieving higher valuations across funding rounds, providing a more granular and dynamic view of startup progression and value creation.

(ii) Unpacking the evolving role of firm performance

By empirically demonstrating that financial indicators related to leverage, liquidity, and operational efficiency become increasingly influential as startups mature, the study emphasizes the centrality of firm-level performance in determining valuation. This finding highlights the shift in investor focus from founder narratives to financial substance over time.

(iii) Reconceptualizing industry context effects

The analysis identifies a non-linear, reverse S-shaped relationship between industry attractiveness and valuation, moving beyond simplistic linear assumptions. Furthermore, the discovery that industry- and firm-level signals act as substitutes challenges conventional additive models and suggests that investors rely on the most salient signals when making decisions under information constraints.

(iv) Revealing the dual influence of investor behavior

The study introduces behavioral finance insights into the startup context by showing how investor overconfidence can distort valuations, while investor syndication serves as a corrective mechanism. This contributes to a more balanced understanding of how cognitive biases and collaborative mechanisms shape valuation outcomes in high-uncertainty environments.

(v) Contextualizing startup valuation in emerging markets

Conducted within the Indian startup ecosystem characterized by rapid growth, increasing institutional support, and high uncertainty, the study offers context-specific insights relevant to policymakers, investors, and founders operating in similar emerging economies. It contributes to a more nuanced understanding of how internal and external signals interact in resource-constrained and evolving market environments.

(vi) Bridging theory and practice through a comprehensive framework

The study builds on existing binary framework of *horse-jockey* and uses the extended *horse-jockey-trainer-meadow* framework to communicate complex valuation dynamics in an intuitive way. This approach not only enhances theoretical clarity but also improves practical accessibility for stakeholders such as entrepreneurs, venture capitalists, and startup advisors.

7.3 Implications of the study

The factors contributing to the success of a business are of interest to innovators, entrepreneurial investment entities, policymakers and other stakeholders. Understanding the dynamics of new venture valuation equips the innovators and investors with the knowledge to evaluate a project's potential pitfalls and prospects before proceeding with the financial commitments. Hence, the findings from this research have several practical implications for entrepreneurs, VC investors, and policymakers engaged in the startup ecosystem.

For founders, the results highlight the shifting nature of investor focus across funding stages. While early-stage investors may be influenced by founder characteristics, sustained valuation growth is more closely tied to financial performance. Startups that build strong fundamentals in areas such as liquidity, profitability, and operational efficiency are better positioned to attract continued investment and navigate later funding rounds successfully.

For VC investors, the study offers insights into how behavioral tendencies, such as overconfidence, can influence valuation decisions. Recognizing the risk of inflated valuations due to biased expectations is particularly important in early-stage investing, where uncertainty is high. At the same time, the positive role of syndication suggests that collaborative investment approaches can introduce checks and balances that improve the quality of investment decisions. Encouraging diverse perspectives through co-investment reduces the reliance on individual judgment and mitigate extreme valuation outcomes.

The study also has important implications for how industry context is interpreted during startup evaluation. The non-linear relationship between industry attractiveness and valuation suggests that sectoral appeal does not guarantee long-term success. Moreover, the substitutive

relationship between firm-level and industry-level signals indicates that strong firm performance can offset disadvantages posed by a less attractive industry. This reinforces the idea that investors prioritize the most salient and credible signals when making decisions, rather than aggregating all information equally.

For policymakers, these findings point to the need for support mechanisms that strengthen firm-level capabilities across sectors, rather than focusing solely on high-growth industries. Investing in more comprehensive and accessible databases can also enable deeper research in these areas, helping scholars and practitioners better understand and support the startup ecosystem.

7.4 Limitations and future scope of research

This research, while offering several important insights into the valuation of startups, is subject to certain limitations that should be acknowledged. First, the study is based on secondary data from a subset of Indian startups. Due to data availability limitations, the sample size is constrained. Moreover, several startup characteristics, such as product quality, patents and other intellectual properties, founder networks, and team dynamics, are difficult to quantify but may significantly influence valuation. The lack of access to internal firm data also restricts the ability to fully capture qualitative aspects that investors often consider during due diligence.

Second, valuation is used as a proxy for success, which reflects investor perception and market momentum, but not necessarily long-term outcomes. High valuations may not always translate into sustainability, or successful exits. Future research could consider tracking post-valuation outcomes such as performance post exit to complement the current valuation-focused approach.

Third, some constructs in the study such as investor overconfidence and industry attractiveness are modelled using proxies derived from publicly available data. While these proxies are grounded in prior literature, they may not fully capture the complexity of investor psychology or evolving market sentiment. Primary data, such as interviews with investors or founders, could provide richer insights into how decisions are made under uncertainty.

Fourth, while this study adopts a broad, cross-industry perspective and controls for industry fixed effects, this approach may not fully capture sector-specific nuances. Valuation drivers can differ significantly across domains such as software, biotech, or consumer technology, where business models, capital requirements, and growth trajectories vary widely. Future research could benefit from more focused, sector-specific analyses or longitudinal case studies to better understand how valuation patterns and investor priorities evolve within particular industries over time.

Finally, temporal dynamics are limitedly modeled in this study. Valuation influences and investor behavior may vary depending on the funding climate, macroeconomic cycles, or regulatory changes. Longitudinal analysis could help capture these shifts and offer more time-sensitive insights into startup valuation.

7.5 Conclusion

This thesis provides empirical insights into how startups can scale their valuations, attract investment, and sustain growth in complex and uncertain environments. Studying valuation is especially important because it sits at the intersection of all key stakeholders' interests. For founders, valuation reflects how the market perceives their firm's growth potential; for investors, it shapes expected returns and risk exposure; and for policymakers, it signals the vitality of the entrepreneurial ecosystem as a whole. By presenting the extended *horse-jockey-trainer-meadow* framework, this thesis offers a clear way to explain the complex realities of startup valuation, bridging theory and practice for the benefit of all stakeholders involved.

This research demonstrates that startup success is best seen as a dynamic process of creating, signalling, and defending value across funding rounds. The empirical findings highlight the shifts from founder credentials to concrete financial performance as ventures mature. The results also shows that investor behaviour and industry conditions interact in complex ways, with strong firm fundamentals able to offset less favourable industry contexts and syndication helping to temper overconfident investor valuations.

These insights contribute to theory by integrating behavioural finance and signal substitution effects into the startup literature, while offering practical guidance for founders, investors, and policymakers. Entrepreneurs are reminded that strong narratives must be backed by sound operational discipline to command and sustain high valuations. Investors gain an improved understanding of how cognitive biases and syndication practices affect firm valuation. The empirical evidence offers pointers to policymakers to strengthen institutional frameworks that support firm-level capabilities.

While this study is subject to limitations, such as constraints in data availability and the use of parsimonious models, it nonetheless offers a solid foundation for future research to expand and deepen these insights.

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List of publications

Manuscripts Under Review in Journals

- Haritha, V. H., Prasanna, K., & Rajan, T., *Signals That Scale Valuation: Decoding the Interplay of Founders and Financials in Predicting Startup Success*. Under review in *Journal of Business Venturing Insights* (ABDC–A; Revise & Resubmit)
- Haritha, V. H., Prasanna, K., & Patel, V. *Picking Winners: Do VC Investors Back Hot Industries or Strong Startups? Evidence from India*. *Journal of Behavioral and Experimental Finance* (ABDC–A; Revise & Resubmit)
- Haritha, V. H., & Prasanna, K. *The Price of VC Overconfidence: How Investor Bias Affects Startup Valuation in India*. Under review in *Applied Finance Letters* (ABDC–B; Revise & Resubmit)

Working papers

- Haritha, V. H., & Prasanna, K. *Navigating the Startup Race: The Influence of Jockey, Horse, and Meadow on Venture Capital Funding*.
- Haritha, V. H., Patel, V., Walker, S., & Prasanna, K. *When to Invest, When to Exit: A Venture Capital Decision Model*.

Conference presentations

- Haritha, V. H., & Prasanna, K. (2025, Jan). From people to performance: Signals that scale startup valuation. Entrepreneurship Research Colloquium 2026, Desai Sethi School of Entrepreneurship, Indian Institute of Technology Bombay, India. (upcoming)
- Haritha, V. H., & Prasanna, K. (2025, July). Do Overconfident Investors Overvalue Startups? Evidence from the Indian VC Market. *World Finance Conference 2025*, Malta.
- Haritha, V. H., & Prasanna, K. (2025, April). *Funding the future: What venture capital investors look for in startups in India and the UK?* British Accounting & Finance Association (BAFA) 2025 Annual Meeting, Belfast, UK.
- Haritha, V. H., & Prasanna, K. (2025, Feb). *Winning the startup race: How founders, finances, and markets shape funding and valuation*. Best Paper Award, Doctoral Colloquium on Financial Markets & Corporate Finance (DCFMCF), IIT (ISM) Dhanbad, India.

- Haritha, V. H., & Prasanna, K. (2025, January). *What Drives Venture Capital Investments? Cracking the Startup Code in India*. 11th Management Doctoral Colloquium (MDC), Vinod Gupta School of Management, IIT Kharagpur.
- Haritha, V. H., Patel, V., Walker, S., & Prasanna, K. (2024, June). *Venture capital valuation and industry dynamics*. 31st Global Finance Conference, Italy.

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