Driving venture capital funding efficiencies through data driven models. Why is this important and what are its implications for the startup ecosystem?

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Doctoral Thesis

Driving venture capital funding efficiencies through data driven models. Why is this important and what are its implications for the startup ecosystem?

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Contents

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Abstract

This thesis aims to test whether data models can fit the venture capital funding process better, and if they do fit, can they help improve the venture capital funding efficiency?

Based on the reported results, venture capitalists can only see returns in 20% of their investments. The thesis argues that it is essential to help venture capital investment as it can help drive economic growth through investments in innovation.

The thesis considers four startup scenarios and the related investment factors. The scenarios are a funded artificial intelligence startup seeking follow-on funding, a new startup seeking first funding, the survivability of a sustainability-focused startup, and the importance of patents for exit. Patents are a proxy for innovation in this thesis.

Through quantitative analysis using generalized linear models, logit regressions, and t-tests, the thesis can establish that data models can identify the relative significance of funding factors. Once the factor significance is established, it can be deployed in a model. Building the machine learning model has been considered outside the scope of this thesis.

A mix of academic and real-world research has been used for the data analysis of this thesis. Accelerators and venture capitalists also used some of the results to improve their own processes. Many of the models have shifted from a prediction to factor significance.

This thesis implies that it could help venture capitalists plan for a 10% efficiency improvement. From an academic perspective, this study focuses on the entire life of a startup, from the first funding stage to the exit. It also links the startup ecosystem with economic development. Two additional factors from the study are the regional

perspective of funding differences between Asia, Europe, and the US and that this study would include the recent economic sentiment. The impact of the funding slowdown has been measured through a focus on first funding and longitudinal validations of the data decision before the slowdown.

Based on the results of the thesis, data models are a credible alternative and show significant correlations between returns and factors. It is advisable for a venture capitalist to consider these.

Introduction

The studies on venture capital financing have all focused on the benefit to the investee, i.e., how an investee, as a founder, receives funding and a favorable valuation. The studies have largely overlooked the venture capital investment process and that the industry needs to improve its efficiency. The National Bureau of Economic Research has published some research papers on venture capital efficiency, but these have focused more on return variability than the core process. This thesis focuses on this research gap that is important both academically and practically. This thesis explores the possibility of venture capital funding to move towards a data-driven, algorithmic model for funding startups.

Recent technology developments such as GenAI, have increased the possibility of use of an algorithmic approach for venture capital funding decisions. In the proprietary models that most venture capitalists use that forms basis for their decisions, limited data is used, and that limits the prediction accuracy. GenAI and large language models will enable prediction of the future growth trajectory with a greater accuracy.

This study is important for many reasons. Venture capital funding and efficiency are closely related to fostering the startup ecosystem. The startup ecosystem, in turn, is often perceived as a driver for new knowledge, and new knowledge leads to economic growth. Thus, funding efficiency across the entire venture capital cycle, from pre-seed to exit, is important.

The importance of venture capital to drive economic growth has often been overlooked. This venture capital enables by funding and fostering startups. *Startups* are a broad brush focusing of knowledge-intensive industries that help build new knowledge and innovation. Innovation has been proven to drive productivity growth and hence economic development. The thesis focuses on both supporting venture capital as a driver for economic growth and a focus on some of the industries that help to create new knowledge. The thesis has identified clear areas where economic and venture capital development are interrelated.

Later in this thesis, we build a case for data-driven funding for venture capitalists efficiency improvements. Patents are studied in the context of innovation and their link with venture capital process efficiency is articulated. The focus on patents indicates that funding innovations is not just a venture capitalists business practice, but also a necessity to drive returns. Emerging, high technology sectors such as artificial intelligence are an essential subject of this thesis. Also, from a practical standpoint, the thesis compares venture capital funding efficiency factors across the US, Europe, and Asia to understand whether the same process can be replicated or whether it needs to be localized. The thesis argues that there are regional nuances and the factors that could help venture capitalists in one region, which may be suboptimal in others.

A significant challenge is that this study attempts to provide alternative solutions for the venture capital industry specific to the funding process. For this thesis, while underlying data models will help predict follow-on funding and survivability, the discussion is on significant factors that will help startups progress toward returns realization by a venture capitalist. The discussion on factors helps in three ways:

1. It helps venture capitalists explore their own models.
2. It provides insights to the entrepreneur.
3. It avoids the broad-brush approach of similar factors for all funding scenarios, regions, and industries.

The case for a data-based model to assist venture capital is based on the following.

1. Fundamental challenges in venture capital industry efficiency need to be addressed. These solutions will include a holistic perspective from first funding to exit. Data-based models will fit this approach best. New advancements in technology such as GenAI strengthen the case further by allowing for unstructured data to be included in the analysis.

2. The industry tends to be cyclical. Cyclical sentiments impact the growth significantly. E.g., in the current negative market sentiment, the investments have been significantly impacted. While the cyclical nature of the venture capital industry is a fact, data models need to capture learning from such cycles and help assuage the impact for subsequent cycles.

3. The venture capital industry performs a more significant function in economic development. The link between startups and economic development is critical. Economic development requires high-technology innovations, which requires the ecosystem of venture capitalists and startups. High technology startups require access to risk capital. Globally risk analytics is becoming increasingly data driven.

4. The traditional corporate finance models fail to address a startups financing and investment needs prompting a search for new model. Traditional capital funding models are based on risk-based capital discounting such as net present value model. Startups risk is dynamic and constantly changes as it progresses. It may improve with traction or worsen with product delays. The dynamic nature of the startup sector lends itself to data-model based strategies.

5. There are different funding strategies for the different industry segments, regional markets, and stages of a startup. Since a venture capitalist normally invests based on a segment or geography expertise, they tend to invest in only some

segments. This specificity forces a venture capitalist towards concentration risk. They would usually invest in the same stage and same industry. For example, some venture capitalists only invest in early-stage AI in Asia. Without adequate portfolio diversification, the venture capitalist may be subject to market nuances and be at a greater risk during downturns. The availability of a data-based model would help them to diversify the risk.

6. There are new regulations that have either been introduced or are being introduced. The SEC regulation mandating greater transparency is in force as of August 2023. Other regions may follow and implement the same. There will be a need for the venture capital industry to progress to more structured decision-making.

Before we proceed, let us define the main players that have been referred multiple times till now.

Startups in this context are defined as temporary organizations searching for a scalable, repeatable, profitable business model (Blank & Dorf, 2020; Blank, 2013). They usually invest in new technologies and processes that could lead to new business models and need initial funding to develop these products for them to evolve into large corporations. The initial funding tends to be riskier as the startups are still developing the products. There is no certainty that the new products and processes can be operationalized internally and will be accepted by the customers. The risky nature of financing limits the funding sources with traditional funding sources not geared for such financing. That is where startups need specialized financing firms, and venture capital fits in.

EIB Institute defines venture capital as a specialized form of financial intermediation that often provides funding for costly technological innovation. Later in this thesis, we will debate whether venture capitalists are best suited to fund technological innovations given that traditional funding solutions, such as direct lending from banks, may not be available. One of the key aspects of venture capital is the long-term nature of investment and that they only make money on what is termed as "exit." Venture capital firms must exit portfolio companies within about five years of the investment to generate returns for institutional investors (Rin & Penas, 2015).

The thesis stresses that the efficiency of the venture capital funding process should be improved, and that can best be enabled through a data driven approach. The statement indicates that the industry may have an improvement opportunity. Next, we focus on the inherent challenges in the venture capital industry that acts as a source of inefficiency. There are three important components of the business problems to be solved. These are high variability in returns, large investments being placed as bets, and current environment and COVID-related changes. The below section probes these in detail.

Inherent challenges of the venture capital industry

The venture capital industry traditionally requires different tools and methodologies for risk due diligence prior to funding but has traditional inefficiencies that must be addressed. To cite some inefficiencies, 65% of the VC investments do not yield a return, the funded startup does not generate positive cash flows during the initial years, the capital is locked in for 5-7 years, and any failure before an exit through either an IPO or M&A, leads to a loss. Further, the industry is dependent on the economy which tends to be cyclical, often leading to downturns. The fact that the investment is locked in periods of five to seven years, makes this industry extremely susceptible during downturns. As per CNBC (2020), the US economy has been in recession thirteen times post recovery from great depression. Greater predictability and better preparedness for downturns would help venture capitalist improve funding efficiency and returns. As per latest Carta (2023) numbers, 20% of the recent raises are at a loss to the last valuation.

Given its implications for the economic ecosystem, the focus needs to be on the industry. The study is also important for entrepreneurs. A better data-based approach will help explain the important features of the startups that may help them get funded. Later in the thesis, we draw a correlation between entrepreneurship, innovation, and economic growth, arguing that support for entrepreneurs should also be a key consideration for this study.

Venture capital returns variability

Large variability is the first challenge to resolved. Later in this thesis, we cover an approach towards follow-on funding and survivability prediction that should be able to increase the predictability.

While variability in returns is endogenous to venture capital investments, the returns are highly skewed, and some form of normalization will help the industry. That normalization is what this thesis attempts through a data-driven approach. To provide more context, let us first understand the challenges of venture capital returns variability.

In the National Bureau of Economic Research publication, Cochrane (2001) has compared venture capital returns to options where there is a small chance of a large return, factoring for exits and closures; various scholars have found varied returns, but the consensus is clear. Venture capital is riskier than the public stock exchange. On the flip side. it tends to return higher than public markets on successful exits.

The word successful exit is critical. In the context of a venture capital investment, exit is either a portfolio sale through mergers and acquisitions or a public listing through an initial public offer. As noted in the previous discussions, the venture investments are illiquid, with a holding period of about five years. Exit triggers investor returns as cash proceeds through M&A or IPO sales. A word of caution. While we do read about the supranormal profits at the time of initial public offer, the returns are measured by economists at a portfolio level. A high return on a particular startup on exit may translate to a low overall return once the returns across the portfolio are normalized. Normalization into average is because many venture-funded startups yield zero or returns that are next to nothing. These will be covered later in this section.

High variability was noted in all the investments. Most scholars have used Beta as a measure of variability. Mullins (2014) has defined Beta as the measure of systematic risk. Beta is a measure of securities volatility relative to market volatility i.e., is the security riskier than the overall market. Stock exchange such as S&P 500 is assigned a beta of 1, and any security with a beta >1 is considered riskier than S&P 500. The security with beta greater than 1 would show a higher fluctuation than the market.

Two things come into play in venture capital. Given the high rate of failure, the Beta is for the venture capital portfolio as a whole and not for individual investments, and returns can only be estimated at exit. Whereas there are rounds of funding between initial funding and exit, these are not marked to market. i.e., the market has not estimated the going concern finances and estimated a value. As an example, the current market (Carta, Q2'2023) suggests that around 20% of the startups are raising funds in a down round. A down round is when funding is raised at a valuation lower than the previous round.

The following example would help explain this better. A hypothetical startup, X raised US$10 million in funding at an overall valuation of $ 200 million in June 2021.

It may be able to raise another $10 million in Nov 2023 but may only receive a valuation of $150 Million. Valuation in this context is the price of selling 100% of the stake. As can be seen, there is a 25% decrease in the startup's value between the rounds of money raised. In the context of venture capitalists, a round that decreases startup valuation noted in the previous raise round is termed a down round. A down round has two implications.

1. The venture capitalists that invested $10 Million at a $200 Million valuation in June 2021 have lost 25% of their investment value. The current value of the startup is at $150 Million.
2. Since startup stocks are not traded, there is no mark to market. Venture capital may discover its value only when the next round is raised.

In the context of the variability measure or betas, Reyes (1990) had estimated betas of 175 mature venture capital funds and reported betas in the range of 1 to 3.8. Cochrane (2001) had an estimated beta of 4.1. Not surprisingly, the lognormal alpha was 68% for the few extremely successful investments. Alpha measures excess return over what the market can return (Ferson & Lim, 2013).

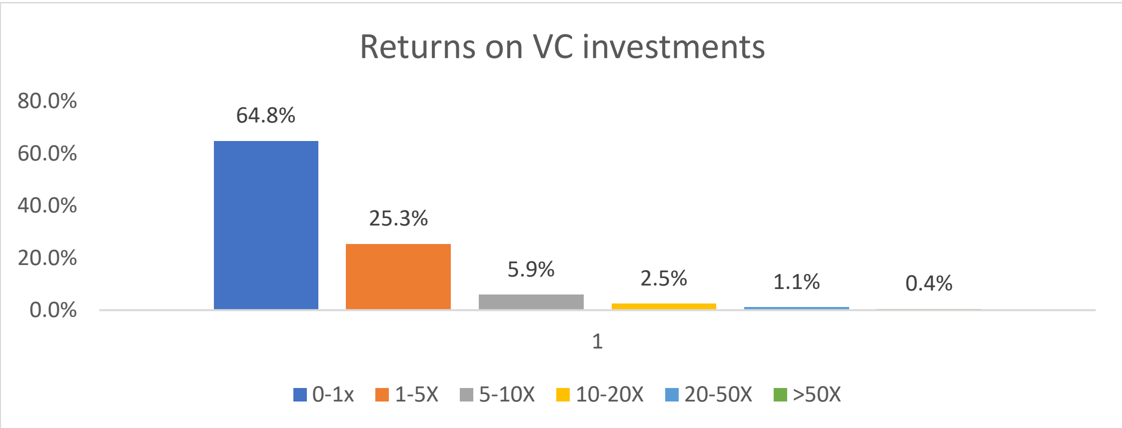
In the context of this study, the new model should increase predictability by reducing the variability of returns. The variability of startups will never be like the public stock markets or other indices. Many startups still need to evolve their business model and have untested technology. The inherent risk and the expected return for a successful startup are higher than existing corporation. The challenge, though, is that venture capitalists are investing both in a successful startup and in one that does not reach an exit.

Improving the predictability of a startup investment would provide a better guide on which startups to fund for the first time and future rounds of funding for venture capitalists. The central paradigm of this thesis is that greater information transparency will emerge from data-driven models, and they should reduce the current high beta levels. Another possible action on this relates to increasing the predictability and survivability of a startup.

Large investments are being placed as bets.

Practical asset managers usually term venture capital investments as putting multiple small bets in the hope that 1% will become unicorns. While some funded deals lead to abnormally large returns, it is important to understand this in the context of Cochrane (2001). Some of these are just options with extremely large payouts. Overall, the US Venture Capital Association (NVCA) data is represented below.

Figure 1 – Returns on venture capital investments for investments between (2004-2013)



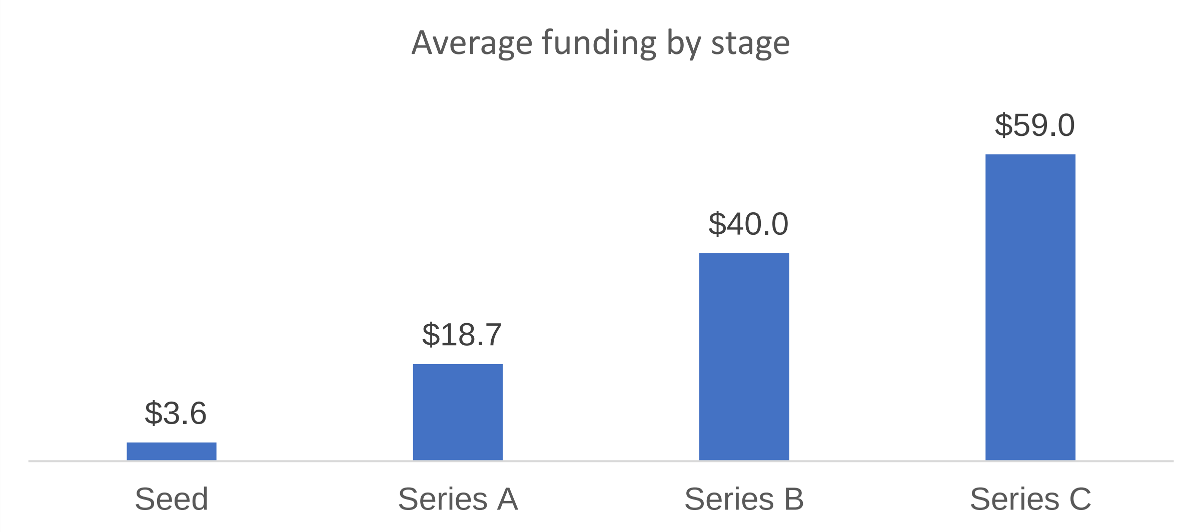
Source: Industry venture (2021)

The curve is highly skewed on the left, with most ventures returning practically nothing. In two-thirds of the cases, the investor is losing part or the whole of the investment. Ewens et al. (2018) have summarized this approach as the colloquial "spray and pray" where the venture capitalist invests in multiple startups providing limited governance. The aim is to identify the few startups that the venture capitalist wants to invest further into, with the rest abandoned after the first few rounds of funding.

Given the return skew and the industry-wide high risk, it is expected that while the data models may not fully normalize the returns, they could shift the model to the right, i.e., reduce the number of startups that show zero or less than 1X returns. The industry would continue to bet on the 1% startups yielding unicorn returns, and the incentive to reduce risk may be limited due to this which is akin to the “spray and pray” mentioned earlier.

Given that the industry was $300+ billion in the last few years (NVCA, 2022), even a slight improvement could be significant in dollar terms. The data models are also important because the median early-stage fund size is $ 75 million in the US (NVCA, 2021) and much lower at less than US$50M globally (NVCA, 2021). Current market estimates are check sizes of US$ 1M to US$ 5M per seed round (NVCA, 2023). At a $50 Million fund size, the fund may need more investment for the statistical return. Also, given the high risk of startups and that most of the startups may not be successful, a venture capitalist should aim at limiting the exposure early if the data predicts a limited success probability. Figure 2 indicates the average fundraising size by stage and shows why it is important to reduce the exposure early.

Figure 2 – Average fundraising size by stage



Source: Visible.vc (2023)

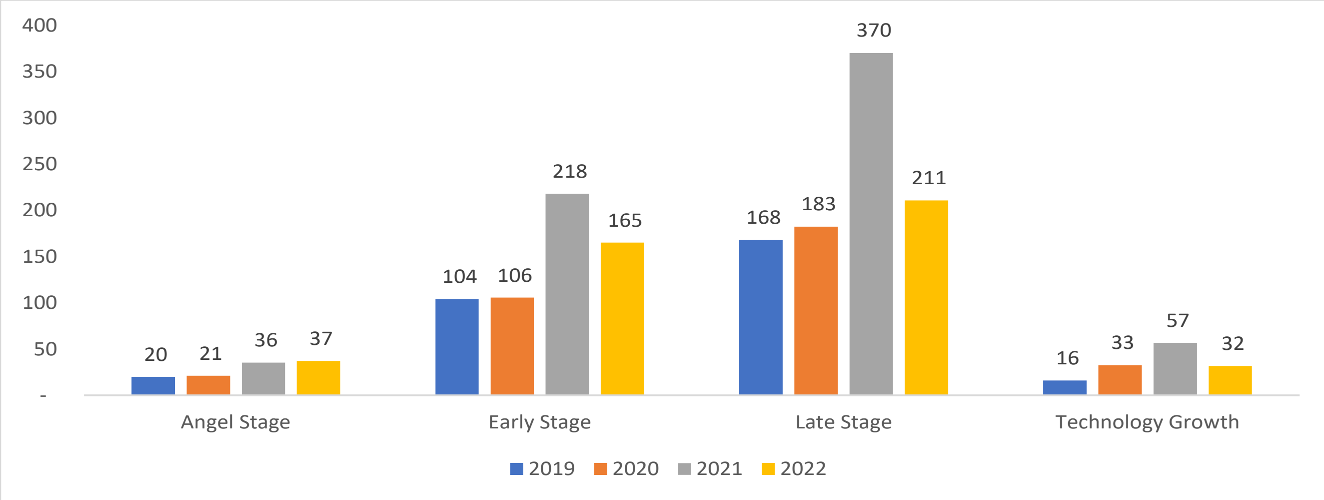
A study from Mulachy (2021) in Harvard Business Review found that out of 100 investments made by Kauffman Foundation in venture capital funds over the last 20 years, only 20 funds outperformed the market to the range of 3%-5%, whereas 62 funds returned less than the average mid-market rate. Kauffman Foundation was a limited partner (LP) in this context. Limited partners are large institutions providing venture capitalists with the funding they need to invest in the startups. Mulachy's (2021) findings are often what is termed as 2-6-2 trend in venture capital where 20% are total losses, 60% funds generate less than market return rates, and 20% outperform the market.

The study from Mulachy (2021) confirms that the current venture capital investment process may not be ideal and may need improvement. The need for change becomes even more significant in the current environment.

<u>Why is there a need for change now?</u>

Market uncertainty resulting from macroeconomic uncertainty has reduced venture capital investments. The need for efficiency increases in a downturn. Consider the following data.

Figure 3 – Global venture capital investments

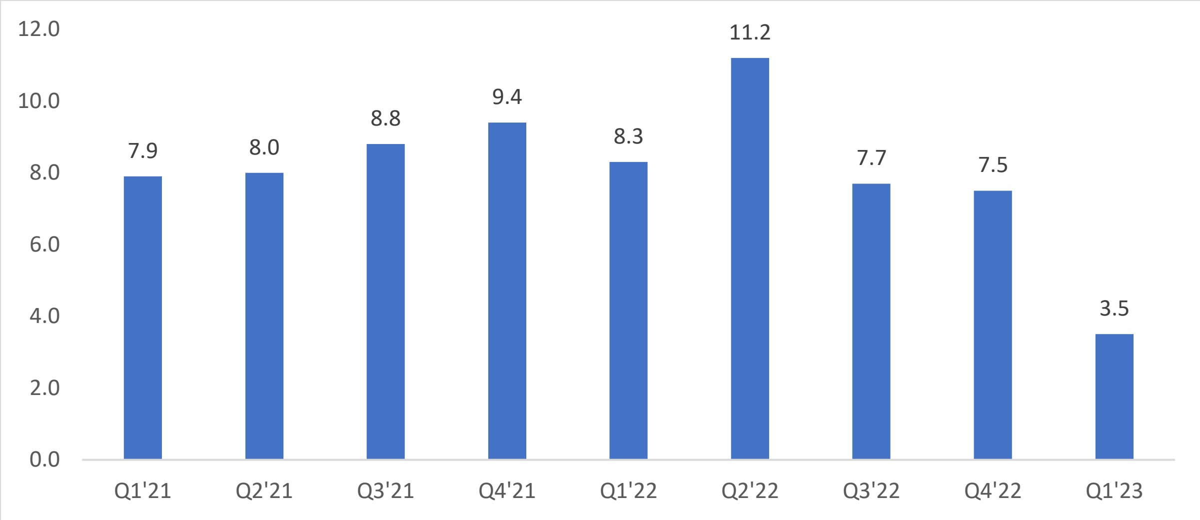


Source: Crunchbase (2023)

Overall, the total venture capital investments declined by 35% between 2022 and 2021. The corresponding decrease by region was a 40% reduction for Asia, a 36% reduction for the US, a 59% reduction for Latin America, and a 20% reduction for Europe. While Asia's GDP grew, Asian investments were still impacted due to China's lockdown. Early indications are of further investment reductions in 2023 (Crunchbase, 2023). Recent SAAS indices (SAAS Financial, 2023) indicate that the valuation of SAAS startups has declined from almost 15X Annual recurring revenue to close to 5.5 X annual recurring revenue.

Bloomberg (2023) has recently published that startup funding is drying up. As per Bloomberg, the venture debt market has reduced, and the latest numbers are as follows.

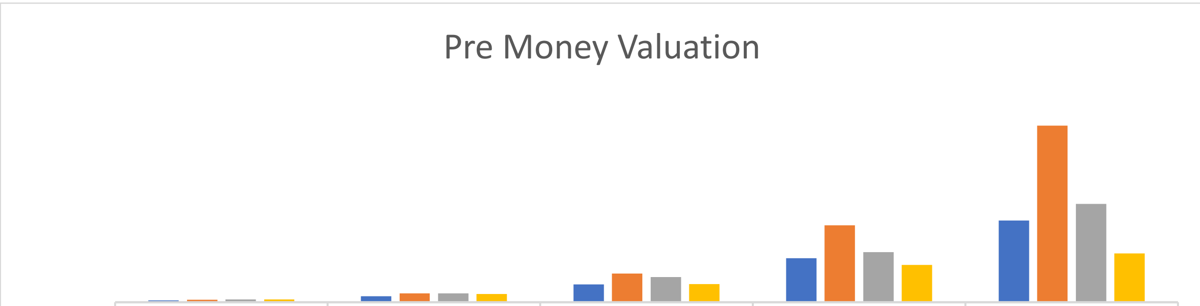
Figure 4 – Global Venture debt trends (2021 – 23)



Source: Bloomberg (2023)

Even the pre raise valuations, valuation of the startup prior to the money raise, have been decreasing. The details are in Figure 5 below.

Figure 5 – Median pre raise valuation by round (2020-23)



	Seed	Series A	Series B	Series C	Series D
2020	$8.1	$27.8	$81.9	$200.0	$372.5
2021	$10.9	$41.0	$130.2	$350.0	$804.5
2022	$13.5	$40.0	$114.9	$228.7	$448.5
2023	$12.7	$37.5	$83.1	$170.0	$222.7

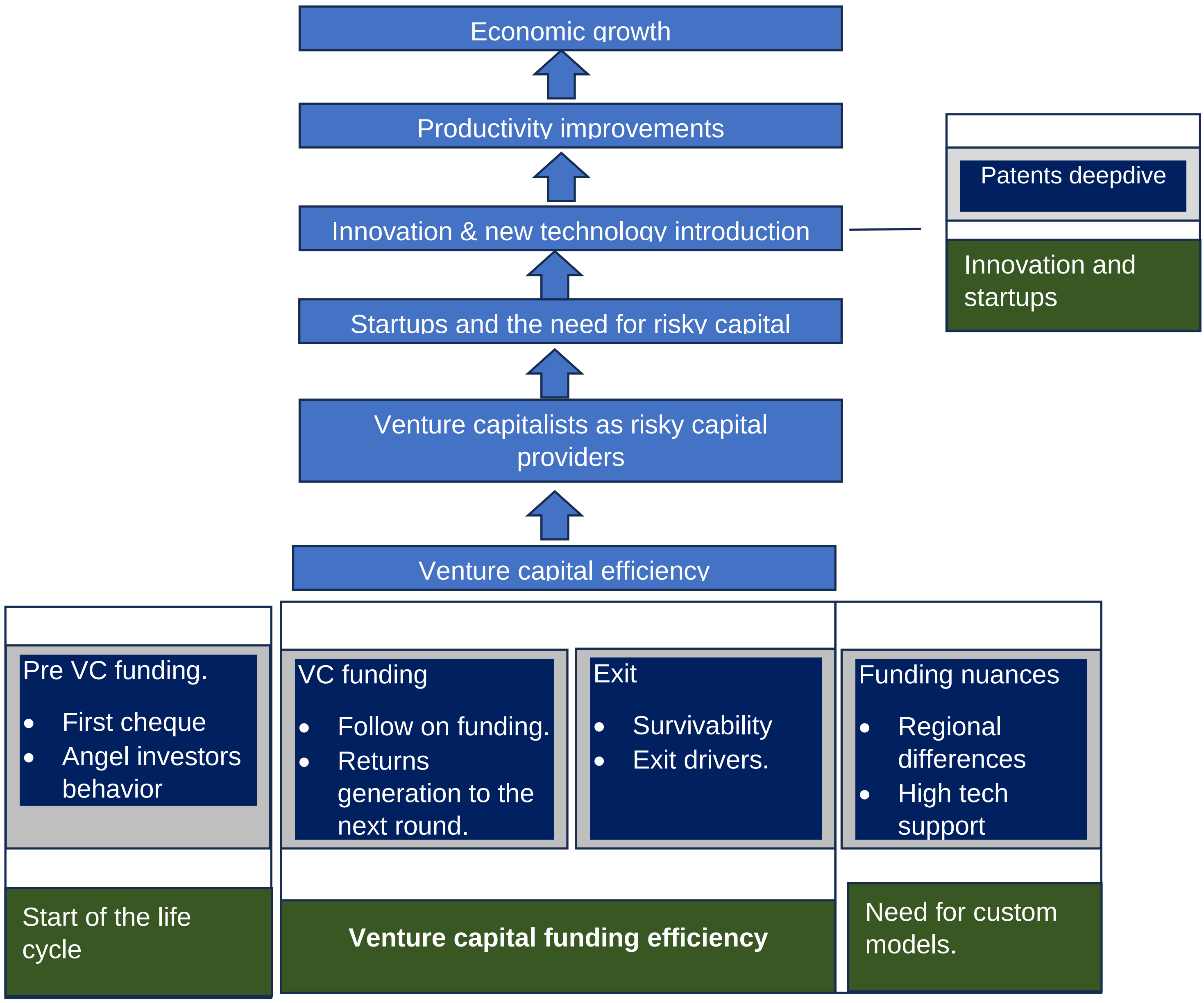
2020 2021 2022 2023

Source: Carta (2023)

The valuation decrease is affecting the venture capitalists in two ways (i) value decrease is more pronounced in the later stages when the venture capital is seeking an exit, affecting their returns, and (ii) in light of the new transparency regulations, the venture capitalist will need to recognize a loss. For example, if the venture capitalist had invested in Series C at a pre money valuation of $350Million and now had to fund a Series D round at $ 222.7 Million, they would need to recognize a 36% loss to their Series C investment.

Unlike in the past when venture capitalists could experiment and bet on startups i.e., “spray and pray”, the current market is forcing them to consider additional methods in their decision-making matrix; now is the time to drive efficiency in the market. Considering this background, the document builds on the need to adopt machine learning models to help Venture capital improve their decisions. Figure 6 explains the aim of this thesis graphically.

Figure 6 – Aim of the thesis



Research Questions

To summarize the findings and the importance of this study till now. While the study has was initiated to focus on the efficiency and returns of the venture capital funds by increasing the predictability of a startup's ability to succeed and survive, it has a larger economic implication.

The priority would be on solving inherent venture capital industry inefficiencies, need to understand factors that could influence funding and returns, studying different stages of a startup growth, and evaluate whether technology plays a significant role in venture capitals risk management.

The following research questions become important in the context of this study:

1. The first question we want to address is whether venture capital investment funding process can be made more efficient. How can machine learning models help to provide better predictability? In this context, we want to review three questions.
    a. Can machine learning algorithms help define which startups to fund? If yes, what are the factors that an investor and investee need to be aware of.
    b. The VC investment process is equivalent to option financing with stage-wise financing. Is there a way to predict which startups are ready for the next round of funding?
    c. The thesis has also discussed that VC investments are illiquid till exit, and exit may be a 5–7-year timeframe. The VC's investment is lost if a startup can survive that duration. Can machine learning help to predict the survivability of a startup?

2. Startups are considered important as they help in the innovation ecosystem's growth. Patents are often considered a leading indicator of innovation. Are they important in the context of knowledge-based startups? Also, it is important to consider the relative importance of other factors.
3. Do the factors that determine which startups to fund vary across the regions? The three regions considered in this study are the US, Europe, and Asia with a deep dive into artificial intelligence startups funding,

For each of these questions, data was analyzed to come to a direction. Specific hypotheses for these factors and related analysis will be covered later. While the problem is practical, it also has a significant academic contribution.

First, the problem has never been broken into these three components.

1. Which startup to fund?
2. When do venture capitalists need to exercise options to increase the stake?
3. What risks do venture capitalists carry to the exit.

Secondly, while there are studies on the individual factors, there is no study that (i) brings all the factors together, (ii) considers it as an industry-specific challenge, i.e., for AI and sustainability, and (iii) considers that factors may vary across regions.

Visually, the study is as detailed below.

Study design

A

Introduction

- The VC industry has traditional inefficiencies that are becoming exaggerated in today’s environment.
- Impact on VC would slow economic growth as VC funds startups and startups help in new technology, leading to economic growth.
- Two priority sectors included in the study – AI and sustainability and their impact on the economy.

B

Research Questions

- VC returns are important for the economy. Is there a data-based way for them to select the startups to fund?
- Is there a way to predict the survivability of a startup?
- Are there specific features that help in funding and survivability? The study considers patents and trademarks as critical variables.

C

Literature Review

- Current research on the link between technology introduction, startups, and growth.
- Importance of funding factors.
- Why patents, AI, and sustainability are important.
- Choosing the right machine learning models.

D

Conceptual Framework

- Research Design
- What machine learning frameworks will fit this study?
- Should the testing be mixed methods?
- Will the tests be acceptable from a practical standpoint?

E

Analysis

- Machine learning model for AI startups. Importance of factors
  - In 2021, the study predicted the fundable startups. The predictions of fundability were longitudinally validated in 2022.
- ML model for a survivability test for an ESG Venture fund was built in 2021. This can again be revisited.

F

Conclusion

- Conclusions and finding significance.
- Academic contribution
- Practitioners' advice
- Future research

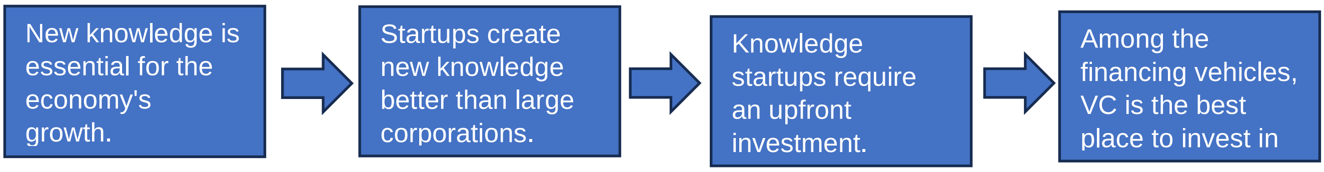
Theoretical Background

This thesis bases the research on the central paradigm that venture capital is crucial for startups and the economy and the process is inefficient. The details were covered in Figure 6, initially, we build on the relationship between venture capital and growth. Does historical research indicate a strong relationship that makes this thesis important?

Importance of the venture capital industry. Why is it important to focus on improving its efficiency?

We started the discussion with a paradigm that venture capital is important for economic development. An easy graphical depiction of this enhanced role can be viewed in the diagram below.

<u>Relationship between knowledge creation and economic growth</u>



In the context of the thesis's central paradigm, it is important to establish the correlation between innovation and economic growth that leads to the need for funding innovation. We also argue in this thesis that innovation is best funded through a focus on startups.

For this, we need to review three aspects of the relationship between economic development and innovation. Firstly, the theoretical framework. What is the evidence that suggests that economic development and innovation are related? We next review the latest findings of the World Intellectual Property Office (2022) that focused on the relationship between economic growth and innovation. Finally, we end with a causal analysis of the relationship between economic development and innovation as identified in a study of 282 Chinese cities.

The theoretical literature has been able to establish the relationship between economic development and innovation. To understand this in context, historical research on this subject has to be considered as the thought process has evolved over a period to support the conclusion that economic growth and innovation are linked.

In the post-Second World War period, the theory of economic growth was based on the Harrod Domar model. The model postulated that growth is only possible if there is an expansion in the natural rate. The model considered labor growth and savings as the critical factors driving economic growth (Solow, 1956). Most nations focused on increasing the labor force either organically or through immigration (the case in the US and Western Europe) or increasing savings (the case in East Asia). One of the basic tenets of Harrod Domar's model was that labor and capital are not substitutable. In the context of Harrod Domar model, innovation funding would lead to marginal benefits.

The first move towards an understanding of the importance of innovation for economic growth was made by Solow (1958). Solow (1958) questioned the assumptions of Harrod Domar's model as the fixed nature of each commodity – labor, and capital, would lead to diminishing returns. Solow (1958) postulated that the nature of diminishing returns would lead to a situation where the capital grows so rapidly that the labor supply would always be short of the target. On the other hand, while labor reaches full employment, the per capita income would fall significantly. For Solow (1958) the only possibility was that more was being enabled by less, i.e. there was a productivity increase that would need to be explained.

Solow (1958) drew the Cobbs – Douglas curve to postulate this argument.

Cobbs-Douglas function was explained by Douglas in the NBER (1967) publication as a model that describes the relationship between production output and production inputs. Labor and capital are the two production inputs included in the model.

In the same paper, A Contribution to the Theory of Economic Growth, Solow (1958) discussed the need to move beyond this diminishing growth and questioned the assumption of constant technology in both the Harrod Domar model and the Cobbs- Douglas function. Solow (1958) studied the correlation of technological change and the growth rate and stated that improved technology would lead to higher output and, as a result, higher savings.

This was one of the first significant works where technology enhancement was considered an important aspect of economic growth. Innovation was an important factor and economies had to think beyond capital and labor and focus on enhancements in technology and innovation as the way forward towards growth. Solow (1958) estimated a technological change rate of 1.5% to arrive at a productivity increase between 1940-49. Solow (1958) also concluded that 90% of the productivity increase between 1940-49 was attributable to technological change and not to additional capital per labor deployed.

Solow's (1958) work created an interest in studying the impact of technology enhancement on economic growth. There was one caveat, however. Explanation of the impact of technology on economic growth was the balancing figure for Solow (1958), i.e., the difference in productivity that a capital increase or an increase in labor could not explain. Later, scholars accepted that technological upgradation would impact economic growth. Mansfield (1972) expanded Solow's (1958) work by introducing multiple factors to increase the explainability of productivity lift.

Mansfield (1972) produced a meta-analysis of the impact of R&D spending on US productivity rates. Historically, limitations in individual studies on this topic reduce their efficacy, and Mansfield’s (1972) meta-analysis provides a more comprehensive insight. The limitations include the inability to segregate the qualitative impact irrespective of whether it relates to product quality, economies of scale, quality of workers’ lives, reduced error, rework rates, etc. Secondly, while R&D data for corporates is available, the data does not specify the R&D activity involved. The R&D activity could be related to improvements in the production process, quality, and inputs. Mansfield (1972) found that while the studies differed in the industry segments and methodologies, they all pointed in one direction: a correlation between research and development spending and productivity growth.

Among the studies quoted by Mansfield (1972) was the study by Denison (1962). Denison included multiple qualitative factors. The most influential of them related to labor quality improvement, as demonstrated by improvements in schooling. Denison’s (1962) comprehensive study explained improvements in productivity to a larger significant extent than Sorow’s (1958) but still has an unexplainable 40% gap. This 40% was attributed by Denison (1962) to technological improvements.

The key message across the studies is the importance of’ technology innovation to drive economic growth, whether we consider that technology impacts 90% of the productivity growth (Sorow, 1958) or 40% of the productivity growth (Dennison, 1962; Mansfield, 1972), economic growth cannot be influenced in the absence of innovation. Technology is positively correlated with economic development and contributes to it significantly. The last seminal paper to be reviewed in this section is Romer’s (1986), “Increasing Returns and long-run growth.”

Classical economists have always proposed the law of diminishing returns, whereas the growth rate should slow down at some point in development. Yet, historically, the world has seen capital accumulation at an increasing pace in many countries, as opposed to almost net-zero growth. If we believe in the classical approach, developed markets with fully exploited labor and capital markets should witness almost zero growth. Yet, we are living in a different reality.

Romer (1986) challenged the belief of diminishing returns by indicating that endogenous technology was one of the phenomena's main hypotheses. While exogenous technology is ruled out, in Romer's (1986) view, the world exists in an equilibrium where endogenous technology changes the long-term growth that is created by knowledge accumulation by forward-thinking actors. Romer (1986) has suggested that knowledge is the basic capital, and that changes the entire long-term growth model.

The importance of exogenous knowledge introduction is also highlighted through a model defined by Kung and Schmidt (2015), who studied the impact on asset pricing in a steady-state equilibrium. Their main finding was that in equilibrium, R&D endogenously drives a small, persistent component in productivity that generates long-run economic growth. In equilibrium, households fear persistent economic growth downturns accompanied by low asset valuations. There is substantial evidence for innovation-driven low-frequency movements in aggregate growth rates and asset market valuations. In short, equilibrium is risky.

Theoretical literature has also drawn an interesting relationship between capital accumulation and innovation. Aghion and Howitt (2017) state that innovation raises marginal returns from capital and thus stimulates capital accumulation. Increasing capital accumulation stimulates innovation by enabling the innovator to monetize his or her innovation. Thus, capital accumulation and innovation are both related and essential to the economy's long-run growth.

Against this theoretical background, let us consider the applicability of the thesis that innovation is critical for growth by considering a practical example. For this illustration, the thesis considered World Intellectual Property Organization's recent publication.

World Intellectual Property Organization (WIPO) is an independent agency under the United Nations that is supported by 193 member states. WIPO publishes the World Innovation Index annually, which ranks the innovation efforts of the nations. The 2022 World Innovation Index focused on the relationship between innovation and economic growth.

World Intellectual Property Office (WIPO) analysis

WIPO draws a correlation between innovation and productivity growth at a country level. This specific relationship is of significant interest to this thesis. The relationship between innovation and productivity then needs to be explored from a practical perspective on how we could be achieving productivity growth, and that question returns to new innovation being introduced. How could we work on increasing innovation quotient for an economy?

WIPO considers both the magnitude and direction of change. Their main finding is that a relationship between innovation and productivity exists. The relationship is nonlinear but has a positive correlation. Some of the key insights are enclosed below.

1. There are three waves of the real-world GDP per capita growth. It was 0.2% in the merchant capitalism phase (1300-1819), 1.1% during the industrial revolution

phase between 1820-1949, and 1.9% during the post second world war phase of 1950-2019.

2. Productivity improvements are the major contributors to improvement in the standard of living during this phase. While it took 50 years for productivity to double before the 1870s and post-1870s, productivity doubled every 25 years.
3. Productivity increases have made a significant impact on the economy for two reasons. One, they have increased personal wealth, and secondly, productivity has been doubling on an increased basis. In comparison to the 1870s, we may be 24 times more productive.
4. The increased standard of living since the Industrial Revolution can be traced back to innovation and invention and the effective diffusion of innovation across the economy.

In the context of our argument that innovation and economic growth are related, this study from WIPO (2022) helps to provide corroborative evidence demonstrating the relationship between historical growth and innovation.

An interesting piece of information from the WIPO (2022) research relates to growth areas. Areas with historically higher innovation investments have shown a faster rate of productivity growth than areas where innovation is difficult. WIPO (2022) data is in Table 7 below.

Table 7: G7 annual productivity growth rates by sector between 1996-2019

	Industry Segment	US %	Canada %	UK %	Germany %	France %	Japan %	Italy %
Leading	Information & Communication	5.4	2.0	8.9	3.8	3.1	2.1	2.1
	Agriculture	4.5	3.7	4.4	3.7	3.4	2.3	1.5
	Manufacturing	3.4	1.7	3.8	2.2	2.8	2.7	1.2
	Wholesale & retail	2.6	2.6	0.6	2.2	1.2	1.1	1.5
	Finance & Insurance	2.1	2.5	1.9	-0.3	2.1	1.3	1.4
	Government	0.1	1.1	1.6	1.5	1.3	1.0	1.2
Overall		**1.5**	**1.2**	**1.2**	**1.2**	**1.1**	**1.1**	**0.3**
Lagging	Transport & storage	0.4	1.0	0.7	1.6	1.4	-0.1	0.7
	Utilities	0.6	1.0	0.0	1.9	0.0	-1.0	-2.0
	Mining	2.2	-0.3	-4.4	1.8	-0.5	-1.2	2.6
	Professional services	1.2	0.9	0.4	-1.2	-0.2	0.8	-1.8
	Health & social services	0.7	-0.2	-0.2	0.7	0.2	-0.9	-0.8
	Restaurants & Hotels	0.4	0.6	-0.1	-0.3	-0.3	-0.9	-0.6
	Education	0.2	0.5	-1.3	-1.2	-1.2	0.4	-0.4

Source: WIPO (2022)

<u>The causal relationship between innovation and economic growth is evidenced by development in cities in China.</u>

To strengthen the case of the need of innovation for economic development, we consider a study that established causality. Our current theories are all based on either correlations or unexplained productivity. Causality will help strengthen the case. In their study of 282 cities, You et al. (2020) established causality between innovation and economic development.

You et al. (2020) identified two data elements to establish the causality between innovation and economic development. Nighttime light remote sensing as an indicator of urbanization. The four pillars of financial investment, human capital, public infrastructure, and academics combined to arrive at an innovation index. The data considered included R&D investment indication, percentage of employees in the third sector, faculty in colleges, academic publications, and patents, among the data considered for this study.

You et al. (2020) were able to establish causality, but they also mentioned that there is a time lag between innovation and productivity growth. Some other scholars have also studied causality and time. Below is a list of some of the other studies that have considered time lag. Time lag is endemic to the cause and effect of innovation on economic development.

Table 8: Some previous studies considered the relationship between innovation and time lag for economic development.

Citation	Model	Scope	Lag time
Dedahanov, Rhee, and Yoon (2017)	Structural equation model and confirmatory factor analysis	140 functional managers of manufacturing in the Republic of Korea, measured via a survey	Three months
Wang and Zou (2018)	Time lag regression analysis	181 wind power industrial policies at ministerial-level 2006–2015	One, two years
Fallah and Lechler (2008)	Conceptual model	Longitudinal data from 10 multinational companies	Two, three years
Frenz and Ietto-Gillies (2009	Truncated OLS regression and Heckman model	Longitudinal data from single enterprises in the UK Innovation Survey	Two years

Source: You et al. (2020)

Granger causality relationship was found at 1% significance for the time lags or one, two, and three years with 3.15 years as the average causality timeline.

There are four conclusions that we can draw from these studies.

1. Whether 40% of the productivity improvement is due to knowledge creation or whether it is 90%, both numbers are significant.

2. Theoretical literature helps establish the relationship between economic growth and innovation with the concept that technology is endogenous but exists in equilibrium with forward-looking workers keen to grow their knowledge base.
3. WIPO (2022) data demonstrated that knowledge-based industries are growing faster, in a study of G7 countries, than non-knowledge-intensive industries.
4. It is possible to establish causality between economic growth and innovation.

The economy would grow when new technology is introduced as an innovation. New technology can be introduced through multiple methods.

1. Large corporates could invest in technology.
2. Technology startups and SMEs would lead the new technology.
3. New technology would be acquired through a third-party source.

Theoretical research indicated that the second option, i.e. “Technology startups, and SMEs would lead the new technology,” dominates. Hence, there is a need to introduce venture capital and to improve its efficiency. We are building on this chain of thought.

Importance of new product introduction

Introducing new products and the new product development process is fundamental to innovation. It is also empirically linked to revenue generation. Consider the following.

Takeuchi and Nonaka (1986) stated that for 3M, 25% of the revenues resulted from products less than five years old. In their 1980s research, Takeuchi and Nonaka (1986) also mentioned that their survey of 700 American companies indicated that roughly one-third of all profits resulted from new products. In 2004, Langerak et al. (2004) analyzed product launches in 128 Dutch firms and found a correlation between new product launches and an organization's performance. Slater and Carver's (1998) study proposed that NPD is one of the core capabilities that converts a market-oriented culture into superior organizational performance. An additional review of theoretical literature also found previous research that showed that new product performance is related positively to organizational performance (Griffin & Page, 1993; Hultink et al., 1998; Montoya-Weiss & Calantone, 1994). The findings seem logical as surveys have indicated that new products drive between a third and half of the revenues. These findings have been cited earlier in this paper.

The finding also seems logical from a practical and corporate standpoint. With increasing competition, a rapidly evolving market environment, and technological obsolescence, it is fair to assume that the organization constantly needs new offerings to maintain and gain market share. Much of it would also require investments in innovation and it is logical to assume that large corporates would be spending a significant amount of their expense budgets on R&D. Yet we find that corporates struggle to produce radical new products.

We need to discuss the best possible strategy for developing these new products at this stage. There are multiple approaches possible.

1. Existing corporations could largely drive the new product creation through their R&D efforts.
2. Startups could champion innovation and new product creation, and corporations could absorb innovation through acquisition.
3. The approach could be mixed, where the corporation invests in a startup through corporate venture capital or co-creates a prototype with the startup.

While it makes sense for a corporation and economy to develop multiple products, some may succeed, while many may fail. The question that arises in a researcher's mind is what role startups play in new product development. The approach would be driven by corporate risk appetite. The question must be addressed in two stages.

1. There are limitations within a corporation that restrict it from experimenting and
2. Startups are driven by different factors that necessitate a focus on innovation. These factors together combine to ensure that startups are important for product development and, as a result, economic development.

Some of these factors are:

Startup business model as the differentiating factor

Business models are best defined as a loose conception of how a company does business and generates revenue (Porter, 2001). Ghaziana and Ventresca (2005) defined it as the way a company's logic of value creation. Broadly, the business model is how the company behaves and seeks to monetize opportunities. The view in this thesis is that intrinsically, an entrepreneur may be more in tune with searching for new opportunities. At the same time, an existing corporation may choose to focus on the existing product lines.

Doganova and Eyquem-Renault (2009) succinctly stated that entrepreneurs' business model is prospective and would entail a future business venture perspective and its value creation logic. A future-oriented business model will not be subjected to quarterly earnings reporting that a large corporation would. Doganova and Eyquem-Renault (2009) also argue that for an entrepreneur, a business model acts as a boundary wall and enables the entrepreneur to provide a flexible mix of narratives and calculations that circulates across heterogeneous actors.

The socialization of the business model endows it with a performative role, gradually building the network of the new venture. By acting as a prospective narrative, defining the boundary walls, and building a vision of the future, it is easier for an entrepreneur to gain acceptance for a new product innovation. In this context, Doganova and Eyquem-Renault (2009) argue that the business model is more than an internal tool; it is a market device, an argument based on the work of Beruza and Guard (2007).

Beruza and Garud (2007) evaluated financial analysts with two lenses. One that has been traditionally maintained is that financial analysts are objective and help demystify a company's accounts and the second states that financial analysts are essentially actors who play a social role in collective beliefs and opinions. They further stress that financial analysts also factor in nonlinear calculations that provide a frame of reference. Doganova and Eyquem-Renault (2009) argue that the business models provide a similar frame of reference to the market. Hence, it is easier for a startup to invest in product innovation.

Similar research on large corporations has provided evidence of why they find it more difficult to invest in product innovation. Kanter, the Ernest L. Arbuckle Professor of Business Administration at Harvard Business School and the founding chair of the Harvard Advanced Leadership Initiative studied this topic in depth and drew interesting conclusions from the practical examples of large corporations.

In his 2007 article, Innovation: The Classic Traps, republished electronically in Harvard Business Review in 2019, Kanter (2019) suggests that large corporations need more success with new product innovations due to how they are structured, i.e., their business model. A classic statement from his article is, "Executives **declare they want more innovation but then ask, "Who else is doing it?"**

Kanter (2019) further elaborates that the innovators in corporations are measured within the same bureaucratic guardrails. One of the quoted examples refers to a case of a consumer goods corporation where only products where market research could estimate the market size and experience could provide a guide on probable success were identified as "innovation" investments. A reader can evaluate the counterintuitive nature of the phrase- innovation is only where experience can provide a guide, and market share can be estimated through research.

Process control also limits innovation in a large corporation's business model (Kanter, 2019). A similar process control lens, as large products, is applied to the startup products. Similar financial returns are expected and sought. An example that Kanter (2019) mentions is the Bank of Boston's investment in a community bank, First Community Bank (FCB).

First Community Bank (FCB) was the first inter-city market bank. While it was an innovation, it was managed by the same management that oversaw the retail division of the Bank of Boston. FCB managers could not convince the Bank of Boston managers that the historical metrics of profitability and accounts per branch had to be tweaked for this offering. As a result, the "deemed" unprofitable branches were closed, making the entire concept unviable.

Conversely, Gillette had maintained a hands-off relationship between its toothbrush (Oral B) and battery divisions (Duracell) and failed to be the first one in the market to introduce a battery-powered toothbrush. Saturn, the autonomous subsidiary of GM, lagged behind GM in some features (Kanter, 2019).

These examples help to elucidate an important aspect of innovation. Large corporations may not be structured to drive product innovations whereas startups are more adept and adapted towards the innovation generation process. The startups are measured by a different set of tools and have a higher acceptance of failure. Since innovation is linked to economic growth and it normally occurs with product and process innovation, it may be detrimental to the interest of the economy to rely only on large corporations to introduce radical new technologies. Hence, going back to our original paradigm, growth needs startups, and startups need funding. Venture capital fits this funding need best as explained later in this thesis. First, let us understand why funding could be critical to this process.

Importance of financing in startup ecosystem development

While new products and innovation are necessary, entrepreneurs need resources to develop the market fully on their own. This constraint is magnified for technology startups that require interdisciplinary knowledge and multiple different aspects to align to create value (Macron & Robeiro, 2021). The limited resources and the need to collaborate lead to an open innovation ecosystem and network effects. The other finding by Stahl et al. (2023) that is critical in this thesis is that the need for open ecosystems often forces startups to partner with large corporations. Partnerships with large corporations are critical both for startups and for large corporations. That is one of the exit strategies that has been discussed in this thesis: exit through either merger and acquisition or aligned with a corporate venture capitalist. While partnerships can play a key role in the startup's development, overall finance is still one of the most important tasks for the entrepreneur.

Tripathi et al. (2019) identified entrepreneurs, technology, support factors, market, finance, and human capital as key enablers for a startup's minimum viable product (MVP) development. Tripathi et al. (2019) found that both the ecosystem and finance were among the critical factors for developing an MVP. From this study's perspective, two important implications will be explored in greater detail in the later sections.

- Finance plays a critical role in the development of the startup, starting at an MVP stage. That helps explain the focus of this thesis on venture capital investments and to help them improve their internal efficiency to be able to generate greater returns for increased financing.
- MVP development requires multiple factors, and so does the growth of a startup. It will be important to consider multiple factors while deciding on which startup to fund.

Before we proceed to the next topic, the importance of venture capital in driving startup growth and innovation, let's complete the discussion with some practical use cases. The below chart shows the value that software startups have created over the period of 2012-21.

Source: Bessemer Venture Partners research (2022)

Why is venture capital essential to drive innovation?

Given startups' importance in driving innovation, the focus now shifts to factors that enable a startup ecosystem. As mentioned before, Tripathi et al. (2019)

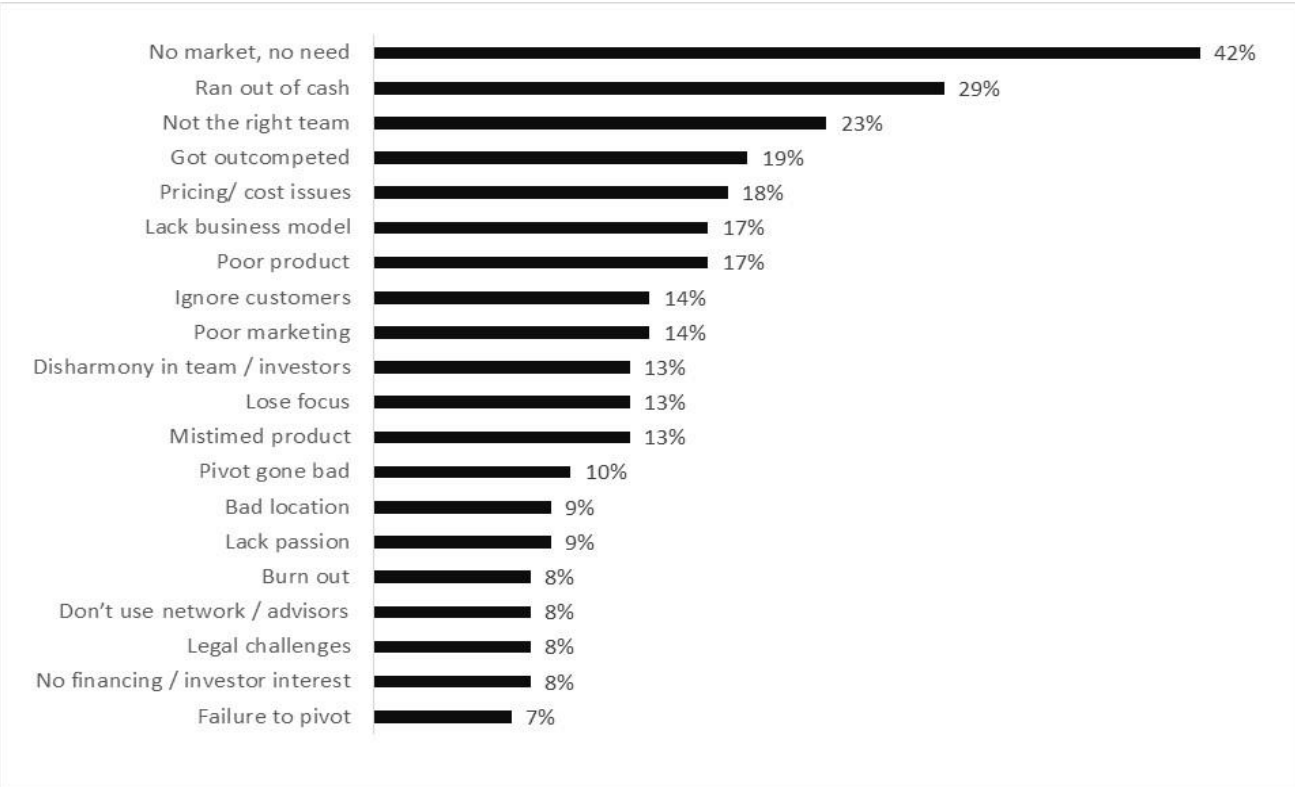
identified entrepreneurs, technology, support factors, market, finance, and human capital as key enablers for a startup's minimum viable product (MVP) development.

Of these factors, this paper will focus on factors that should enable financing for a startup that would lead to greater efficiency and returns for the venture capitalist. In this context, venture capital is a type of financing that supports high-technology and rapid-growth startups. But before that, let's consider the following.

Role of Financing in a Startup's Success.

The thought has plagued social scientists, policymakers, venture capitalists, and entrepreneurs as to why some startups fail while others succeed. Of course, there are no easy answers to this question. CBNInsights (2018) attempted to address a part of this question by conducting a postmortem of 101 failed startups. Their finding was as follows.

Figure 9 – Top reasons for a startup failure



Source: CBN Insights (2018)

Three of the reasons for failures related to financing, including the second highest reason of running out of cash at 29%. The other reasons included disharmony with investors at 13% and a lack of financing or investors at 8%.

In its policy brief on inclusive financing for startups, the OECD (2014) identified improving access to finance as a critical enabler for entrepreneurs lacking finance as a common barrier for new enterprises. OECD's (2014) study included an analysis of the Global Entrepreneurship Monitor (2012) database study across 15 EU countries for lack of financing as a reason for entrepreneurial failure. The percentages varied as high as 36% for Hungary to close to 5% for the UK.

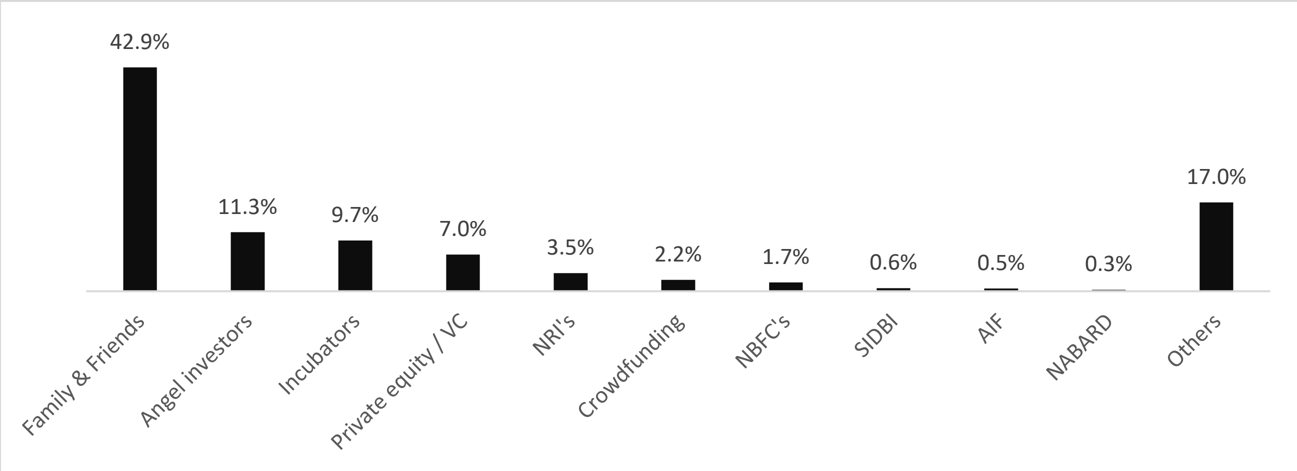
Vandenberg et al. (2020) capture the need for startup financing well, especially as it applies to high-technology startups. They studied the impact of funding for Cleantech, Agritech, Edtech, and Healthtech startups in India, Cambodia, Thailand, and Vietnam.

In their publication, "Financing for tech startups in Selected Asian Countries," published by the Asian Development Bank Institute, they called finance the central component. Vanderberg et al. (2020) stated that inadequate finance will limit the potential of startups. Access and importance of finance for these startups must consider the following dimensions (Vandenberg et al., 2020).

1. These high-technology startups are critical for growing innovation and economic growth. There must be multiple sources for funding these.
2. High technology usually involves significant upfront investment. Entrepreneurs may need independent sources of funding beyond their funds.
3. The selected sectors usually have a long gestation period till they become profitable.

While venture capital is not the only funding mechanism, it may be the most suited for this thesis. Consider funding alternates identified by Vandergerg et al. (2020).

Figure 10- Source of startups funding, India



Source: Vanderberg et al. (2020)

Not surprisingly, Vandergerg et al. (2020) found that venture capital was not the primary funding source for the startups in their study. As stated earlier, only less than 0.5% (Janeway et al., 2021; Puri & Zarutskie, 2012; Lerner & Nanda, 2020) of the startups are venture capital funded. The important question is not whether many of the startups are being venture capital funded but more on what are the venture capitalists funding? This limited venture capital funding can be explained based on Kerr et al. (2014) findings that VC is attracted to “capital-efficient “ sectors for experimentation and subsequent scaling up.

Kerr et al. (2014) finding is critical in the context of this paper. Funding will typically be available for software and IT-enabled processes where we expect most of the recent innovation and impact on economic growth. There are two operational words in Kerr at al. (2014) statement.

1. The startup is still could be in the experimentation stage and hence carry an operational risk. Even the later stage startups still need to return to the venture capitalists through exits.
2. The venture capitalists are betting on scaling up as the main driver of the expected return. They are in the risky beta territory (startup risk is much higher than the market risk and hence is their ask for a return).
3. It can be argued that venture capitalists are best placed to fund these startups. Of course, as discussed earlier, such funding would have an intrinsic risk attached and that is where this thesis is highlighting the need for the funding decision to be data-driven so as to help improve the predictability.

The ability of Venture Capital to invest in risky assets makes it the innovation financing engine.

Historically, less than 0.5% of US startups are backed by venture capital, but venture capital-backed startups contribute 50% to the new firm IPOs (Janeway et al., 2021; Puri & Zarutskie, 2012; Lerner & Nanda, 2020). By analyzing these figures, a reader may note that venture capitalists play a significant role in the startup ecosystem development; they will be right. The startups have been able to scale up in a period of 5-7 years on average (NVCA, 2022) to become significant players with tradeable market value. The innovation has gone beyond the MVP and initial launch to an industrial acceptance. But that is the reason that venture capital industry was created; to boost innovation and to invest in experiments that will not find alternative funding.

Venture capital was created to boost new technologies and innovation. Historically, the birth of venture capital in its current form dates to 1946 (Metrick & Yasuda, 2021), and it is attributable to General Doroit. In the 1940s, during the world wars, innovation was needed but limited by bank lending rules. Banks needed evidence that borrowers had collateral and could make timely interest and principal payments. The absence of collateral led to the concept of risk capital, i.e., where capital that carried a high default risk could be provided.

Most entrepreneurial firms could not guarantee payments or provide collateral, so they required risk capital in the form of equity. General Doriot recognized the need for risk capital and created the American Research and Development Corporation (ARD) to supply it (Metrick & Yasuda, 2021). The firm began operations in 1946 as the first genuine venture capital firm.

ARD proved two important VC concepts. Firstly, you could generate supernormal returns by investing in risk capital. ARD generated 15.8% returns. Secondly, you need moonshots. Digital Equipment Corporation (DEC) was ARD's moonshot. To date, these two concepts remain the basis of the VC industry. High returns with high variability. The reader may remember that the high variability is immensely interesting to the thesis.

Our central paradigm is that the mix of human and data-based approaches would help bring greater predictability and reduce some of the variance by understanding the data patterns from historical funding and investments. As will be discussed later in the thesis, there have been attempts to understand these but most of the work has focused on helping entrepreneurs raise the money and not on improving venture capitalists' efficiency. While the thesis has formulated models and demonstrated that a data-based approach is possible, the improvements could be more drastic with the introduction of new technologies such as GenAI.

A venture capitalist's role in developing the startup ecosystem is linked to its financial and returns model. A venture capitalist comprises two players: a General Partner (GP) role and a Limited Partner (LP) role. A GP decides on the funding decisions and acts as a fund manager, whereas an LP provides the capital for the GP to invest. Usually, a GP’s compensation is around a 2% management fee and 20% carried interest (Metrick & Yasuda, 2021). Carried interest is a venture capital term that refers to the investment gains at the time of exit when the investment is on a venture capital book. For example, if $ 100 gains are made in an exit, as per the venture capital terms, $80 will flow back to the LP, and $20 will flow to the GP as fund manager.

It is in a venture capitalist's s interest to invest in small companies that have the potential to scale up rapidly to maximize their returns and compensation since they get a percentage of the investment gains Thus, in addition to what was indicated by Kerr et al. (2014), other scholars have also indicated the need for startup to focus on an innovative business product or process. To qualify for venture capitalists’ investment, a company usually needs some innovation (Metrick & Yasuda, 2021). Similarly, a venture capitalist gain maximization focus drives it to build a startup ecosystem and foster innovation. Further empirical evidence for the same was provided by Popov and Roosenboom (2013). They studied evidence from 21 European countries between 1998 and 2008 and found a correlation between VC and new business creation. The symbiotic relationship between startups and venture capitalists where venture capitalists want to foster an innovative ecosystem, and startups understand that they need to innovate to be funded, creates the innovation impetuous.

How do VCs help develop innovations?

A venture capitalist can invest risky capital and consider an investment over a 3-5-year period.

A venture capital adopts a multi-stage startup funding model, equivalent to conducting experiments. Venture capital funding is like buying real options. A venture capitalist can abandon the investment if the initial prospects appear poor. On the other hand, they have the right to invest more money into the next stage of financing should initial prospects seem promising (Cornelli & Yosha, 2003; Bergemann et al., 2011). On top of the option pricing, the venture capitalist often assumes a part of the managerial duties by becoming a part of the board of directors. This option pricing model is the one that we are leveraging in this thesis by estimating new risk at every funding ask and evaluating fund 'ability' based on a data driven approach. In addition, the thesis is also suggesting a survivability test that would help protect a venture capitalist returns.

By enabling the development of new technologies by providing small amounts of risky capital and participating in the startup's management, venture capitalists become innovation facilitators (Timmons & Bygrave, 1986; Faria & Barbossa, 2014; Yang et al., 2023). Popov & Roosenboom (2013) also help in explaining this.

As per Popov & Roosenboom (2013), there are three ways in which venture capitalists help a new firm create and foster innovation.

1. A venture capitalist helps establish a new firm directly by providing seed capital. In this new firm, the venture capitalist ensures that good ideas are funded even though entrepreneurs may have conceived them without capital.
2. Entrepreneurs are aware of the venture capitalists' multi-stage funding approach and will only exert efforts on ideas that can show regular traction.
3. Gomper et al. (2008) have indicated that the presence of a younger publicly traded firm and venture capital leads to entrepreneur spawning. More employees

will likely form their startups and contribute to the innovation ecosystem. Silicon Valley is an example of entrepreneur spawning.

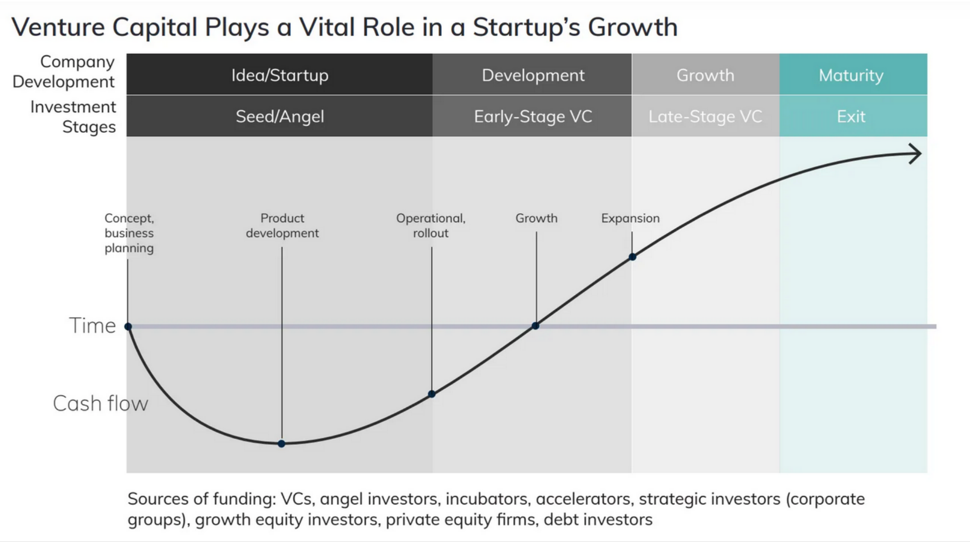
We consider two additional studies to provide further evidence of the relationship between venture capital and innovation development. Faria and Barbossa (2014) studied the relationship between patent filing and venture capital funding in 17 European markets. The relationship was significant.

Interestingly, even Faria and Barbossa (2014) considered a Gaussian Mixture Model (GMM) rather than Ordinary Least Squares (OLS), as OLS models did not fit the data. This thesis also leverages GLM (General Linear Model) as OLS models were rejected based on Kolmogrov-Smirnov tests.

Yang et al. (2023) studied venture capital's impact on innovation in China. To address the regional innovation and entrepreneurship imbalance, since 2015, China has established fund towns. Fund houses promoted the introduction of venture capital to establish an innovation ecosystem and promote entrepreneurial contribution to the real economy.

Yang et al. (2023) used a sample of fund towns from 2012 to 2019 as a quasi-natural experiment and found that fund towns positively affected local innovation. The increasing investments by venture capital firms helped establish innovation ecosystems in the fund towns. Additionally, the spillover effect was identified where the innovation in nearby cities increased after the establishment of fund towns. The relationship between the cash flow of a startup and its development stages is best represented below.

Figure 11- The need for risky capital in a Startup. The initial cash flows are negative.



Source: Venture Forward (National Venture Capital Association) – 2023

There is a need to focus on artificial intelligence and sustainability in this thesis.

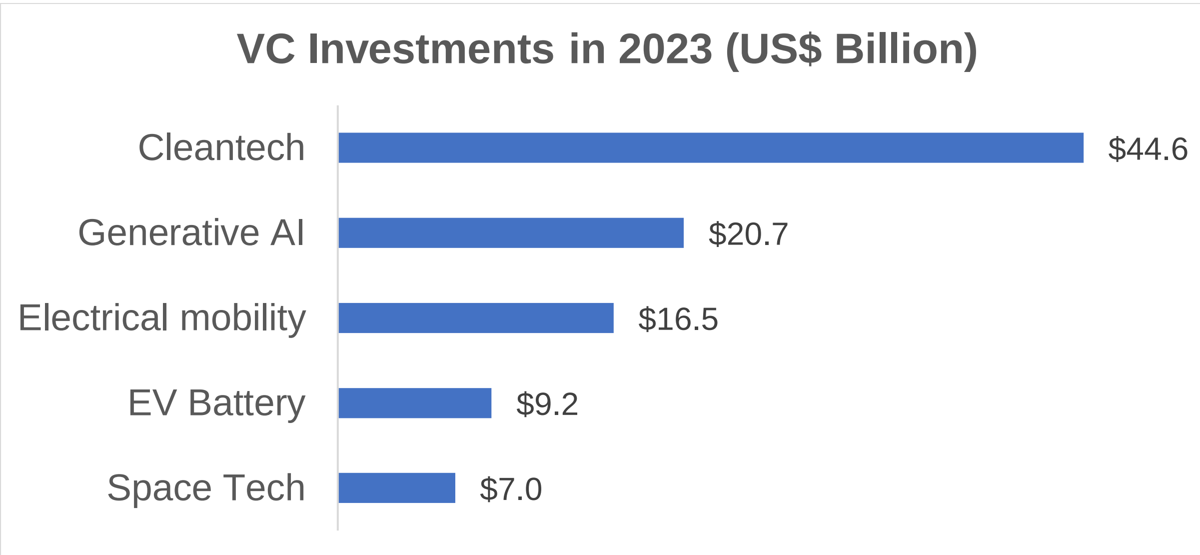
One of the key aspects noted earlier is that this study would focus on two segments- artificial intelligence and sustainability. There are multiple reasons for a focus on these two segments.

1. Many of the other attempts at finding significant factors ignore industry characteristics. This will be discussed later in this thesis. From data aspects, the thesis has seen an increased accuracy in both significant features and models when the industry-specific characteristics are included.
2. Different industry segments have different funding needs. For example, a DeFi solution needs much more money than artificial intelligence software. Even in artificial intelligence, deep tech requires higher funding than normal machine learning solutions.
3. The business models are at different stages of readiness. Even between the two segments, most of the artificial intelligence use cases are focused on automating an existing process. The saves and the impact are easier to estimate. Compared to the artificial intelligence segment, sustainability is aiming to create new

business models, such as solar power instead of regular power. From a venture capital perspective, there are very different underlying risks.

Both these segments have been included as they are fundamental to the discussion in this thesis, where startups lead to economic growth. Artificial intelligence focuses on innovation and new technologies, is a scalable sector, and will be in the sweet spot for most of investors. “Sweet spot” is an investment term where the venture capitalist is most comfortable investing. Sustainability, on the other hand, requires significant project capital, is an existential threat, and business models are not that easy to identify. Both these segments have been on most Governments policy focus and are being funded. These segments were also chosen as these are the top investment areas for venture capitalist in 2023. Consider figure 12.

Figure 12- Top investment areas for venture capitalists in 2023



. Source: DealRoom– 2023

The next stage is to understand these segments in a slightly greater detail. Artificial intelligence, as defined by the European Parliament Briefing (2019. This is a downloadable pdf; the link is in the references), is a term used to define machines performing human-like functions such as learning, reasoning, understanding, and interacting. AI can take the form of technical infrastructure (such as algorithms), be a part of the production process, or be a product by itself, such as bots. As per the briefing, AI is one of the key drivers for growth that will double the economic growth rate by 2035. The Oxford Dictionary defines algorithms as rules to be followed in computation or other problem-solving computations.

Concerning Asia, Asian Business Council (2017), for large Asian developed markets, the investment-led, labor and resource-intensive growth model that fueled the “Asian Miracle” in the past decades is now obsolete. Further, for the growing Asian economies like China and India, the need to grow driven by cheap labor can be replaced with a technology and AI-driven approach that may benefit the growing middle class and enable these markets to develop and advance. Similarly, in the US, the State Department (2021) for the US Government has stressed the need for the US to maintain leadership in AI. While Governments have stressed the need for Artificial Intelligence, previous research helps explain that startups are critical for developing revolutionary technology, which will also hold for Artificial Intelligence.

The 1987 United Nations Brundtland Commission defined sustainability as “meeting the needs of the present without compromising the ability of future generations to meet their own needs.” (UN, 1987). Sustainability not only helps protect the environment, but it may also directly impact economic indicators.

Sustainability is not just about environmental protection but building a new business model that supports net zero. There are reported examples where such a business model is possible. For example, Malesios et al. (2018) found a significant Bayesian regression covariate between an SME's sustainability efforts and financial performance in their study of 119 SMEs across Europe and India. Similarly, Addai et al. (2023) proved causality between environmental sustainability and economic growth from an Eastern European context. Meanwhile, Rahat and Nguyen (2023) found empirical evidence to prove that even in the mining sector, which is often tagged with negative environmental connotations, ESG and financial performance are positively linked.

Both sustainability and artificial intelligence are also important as they are often implemented together to create an impact. The impact, in this case, is to reduce the carbon footprint. Holger (2023), in a recent Wall Street Journal article, explained this well. Since buildings cause 26% of energy-related greenhouse emissions, JLL, a top developer, has invested in AI systems to help predict usage and reduce utilities automatically.

These two business areas converge well with the intent of this thesis. Which is to help venture capital firms improve their efficiency so that they can fund growth. At this stage, it must be mentioned that.

1. The discussions in the case of artificial intelligence startups will be on follow-up funding. Artificial intelligence project size can vary as detailed earlier, and it may need option-based funding regularly. In the analysis of the US startups, the 81 AI startups raised funds at an average of every 1.5 year. Given the frequency of raise, this segment will be evaluated for follow-on funding. The venture capitalist would be exposed to frequent risk and due diligence requirements.

2. The discussions in the case of sustainability startups would be on survivability. As mentioned earlier, the sustainability project size tends to be larger with a higher exposure to the venture capitalist.
3. Funding factors would be discussed to provide a view of what could be critical. Between survivability and follow-on funding, the thesis aims to provide a slice of guidance for the possibilities. A venture capital general partner can decide to implement his own data model. The other business segments could be the subject of another study.
4. Specifically for artificial intelligence startups, the presence of a patent and the likelihood of an IPO has been studied.

Besides these segments, the first funding has been covered as a use case. Given the current sentiment, it is good to give advice to the entrepreneurs.

The need for a data driven model to estimate feature importance.

Next, we look at why we need a data model or a different model to estimate the funding risk and to conduct due diligence. Both financial theories and venture capital funding are not new subjects, and historical frameworks exist. This thesis intends not to build a new framework but to derive one based on historical and practical information, keeping in perspective the nuances within venture capital funding.

The circumstances to be considered are the fact that:

1. Venture capitalists are essentially funding a startup with negative cash flows and where information is private, they have developed their own models and heuristics.
2. The classical segregation between investments and managements are blurred. The investors could be on the board of the startup.

Applications of the net present value methods is one of best example of the difference between a startup funding and that of a large corporation. The below details refer to the work of Professor Damodaran, one of the leading authorities in financial valuations.

Net Present Value Method

Net Present Value is the most used method for an existing, profitable corporation. The value of a corporation is its ability to generate cash, and historical cash flows are the best indicator of future profitability. There are challenges in valuing a startup using this method as it has negative cash flows during the initial phases of its operations. Figure 11, depicted earlier in this thesis explains the cash flow estimates of a startup from cash negative to cash positive.

Damodaran (2019) converted the cash flow estimates into challenges for funding. The below Table 13 explains this.

Figure 13- Cash flows at different stages

	Startup or Idea Company	Rapid Expansion	High Growth	Mature company	Decline
Revenue / Current Operations	Nonexistent or low-income/ Negative operating income	Revenues increasing / income still low or negative	Revenue in high growth / Operating income also increasing	Revenue growth slows / operating income still growing	Revenue and operating income growth drops off
Operating History	None	Very limited	Some operating history	Operating history can be used for valuation	Substantial operating history
Comparable firms	None	Some, but in the same stage of growth	More comparable, at different stages	A large number of comparable at different stages	The declining number of comparable, mostly mature
Source of value	Entirely future growth	Mostly future growth	A portion from existing assets/growth still dominates	More from existing assets than growth	Entirely from existing assets

Source: Damodaran (2019)

Before we go further, two important concepts must be clarified. (i) the concept of fair value, and (ii) while the thesis focuses on funding drivers, the relationship between funding and valuation and what makes valuation an important concept in the context of this thesis.

Value and funding are correlated topics. Value is the total price that is being assigned to the asset, and funding is the money that is being spent to buy a percentage of the value. In this context, valuation is a notional value, whereas funding is real money that is being spent to acquire a percentage of the value. Venture capital invests in real funds, and hence, an understanding of where and what to fund is important for venture capital's growth and efficiency. The concept of valuation is also critical as eventual venture capital returns are subject to the value attached.

Consider a recent example of the Instacart IPO (APNews, 2023). The startup was valued at $ 39 billion in 2022. Its current IPO was a $ 600 million raise at $30 a share, leading to a total value of $ 10 billion. This transaction explains the difference between valuation and funding. A total of $600 million was invested in the IPO as real funding, whereas notionally, the startup has lost value from $ 39 billion to $ 10 billion. A VC that would have invested at a $ 39 billion valuation would have lost money, like the example of the down round mentioned earlier.

Many experts, including Damodaran (2019), stresses that the net present value should be the only method used, even for startups, the thesis argues that the method may not fit startups as the startups lack operational data. Consider the following:

1. A VC, while funding, will need to estimate the time for a startup to reach maturity and the cash flow it could realistically generate at that stage for its going concern

value. Given that the VC would expect to hold an investment only for 3-5 years, the startup will need to scale up significantly and rapidly.

2. Estimates should be made about possible cash flows and growth. Estimates are where a data-driven approach would help drive objectivity. In Figure 13 above, the comparable role could start as early as the expansion stage. As per Figure 11, that is when the startup reaches out to early-stage venture capital for funding.

3. The investor must estimate risk. Since the businesses are pre-revenue and in an expansion phase, the risk would depend on the business model and its enablers. Currently, the risk is being assessed based on heuristics. This thesis proposes that the model evolve to one backed by data that will be tested based on startup data.
4. As stated earlier, venture capital financing model is akin to option pricing model. The financing has to be considered akin to buying a new option at every funding stage. As indicated earlier in the thesis (i) the startups tend to raise funds every 1.5 years based on a sample of 81 US artificial intelligence startups, and that means a new risk evaluation every two years, and (ii) the market and economic ecosystem is dynamic and changes in the economy may affect the startups risk evaluation. Plus, there is a greater need for transparency as stipulated by recent regulations. Data based models especially the ones that leverage latest advancements such as GenAI, will fit the model best.

A reader may question that some of the challenges could be same for larger corporates and startups. Why do we need to we need the financing and funding policies vary. The different models between large corporate financing and startups introduce different business risk, and these need a different approach to due diligence. The difference between a large corporation financing and a startup financing is best understood with a short summary on entrepreneurial finance; the stream of finance that has been developed to manage startups.

Entrepreneurial Finance

Early-stage financing often falls within the realm of entrepreneurial finance. Many differences exist between an early-stage startup's financing needs and a large corporation's, which necessitates a separate discipline. Of the differences, eight are significant differences covered in Entrepreneurial Finance (Smith & Smith, 2004). These are:

Interdependence between investment and financing decisions

In traditional corporate finance, investment and financing decisions are considered independent, but not so for startups and entrepreneurial finance. In a large corporation, the investment decision will be based on a returns comparison between different opportunities and the market rate of return. A manager will choose the option with the highest return. A startup may need to raise funding to complete an investment. In that context, the business case may not just be subject to the objectivity of returns but also from an investor's point of view. An investor must be convinced of the business case the startup wants to initiate. More specifically, since a startup does not have sufficient assets, investment choices are contingent on financing choices requiring the startup to be attractive to the investors.

For example, a recent article in Business Times (2023) wrote about a startup, Circular, raising $7.6 Million to fund expansion in Singapore and Australia. Circular fund raise is a good example of the discussion above. In this case, money was raised to invest in two markets. It would be safe to assume that Circular may not have been able to invest in Singapore and Australia if they were unsuccessful in raising the funds.

Diversifiable risk and investment value

The risk associated with a startup is much higher than that associated with a large corporation and is the largest difference. To add to this complexity, the investors and managers often differ on the quantum of this risk within the startup. The manager may believe an investment is low risk as he and his team have previous experience with the use case. On the other hand, an investor may have a differing view on the same investment and may need additional proof points before deciding on the investment. This differing view on risk affects the diversifiable risk assumptions and estimates of investment returns required.

In project finance, risk measures are applied only to undiversifiable risks. The rate required for a project to be funded is lower for a large corporation than for a startup. For startups that want to finance a project based on the funding and create a revenue stream based on the project, the project is probably the only revenue stream whereas for a large corporation, there are other revenue streams and project is an incremental revenue stream. If the project fails for a large corporation, they still have a business model to fall back too. That may not be the case in a startup.

A higher financing hurdle rate for a startup implies that fewer projects are funded, and investments need to be considered more as options with multiple funding thresholds. A high financing hurdle and risk expectation is why the same project may be initially funded as seed, find early adopters in early-funding rounds, and be scaled in late funding stages.

Wework is a recent example that exemplifies this case (Jane, 2019). In the case of WeWork, the understanding of diversifiable risk differed between investors and the founder (Adam Neumann). To indicate that the risk was lower, Wework coined a new term, community EBIDTA, that subtracted some of the expenses they felt were being deployed for community building, such as amortization, marketing, and interest. It turned out that the founder's estimate was incorrect, and it could not prevent Wework from filing for bankruptcy in 2023.

WeWork is not an isolated case where the estimates of diversifiable risks vary. Startup history is full of these cases, and this risk is intrinsic to startups and venture capital investments. Most startups are defining a new business model, which can often lead to failures. In the context of funding, the difference in risk could lead to a situation where investors want a larger share of the startup (percent of shares offered to them in return for funding), and that may not be acceptable to the founders. Later in this document, we cover a case of Shark Tank crowdfunding that would provide a greater narrative around this example.

Managerial involvement of the investors

There is a fundamental structural difference between large corporates and entrepreneurial ventures. In large, publicly traded corporations, an investor can exit the company anytime by selling shares on the stock exchange. Since entrepreneurial ventures and private equity are not traded, the risk for an investor increases significantly. An investor may realize the return only when a privately held company initiates a public offering or is offered for acquisition.

The investor is locked in with a privately held company until that period, which could be many years. As a result, there is a difference in an investor's involvement with the startup's management. In traditional corporates, investors are rarely involved in managerial decision-making. That does not apply to entrepreneurial ventures. Fundamental differences in corporate structure and harvesting opportunities drive venture capitalists and angel investors to demand a role in the organization's management.

Angel investors and venture capitalists often demand a board seat and are known to initiate organizational structure changes where they are not satisfied with the progress. A managerial role also implies that the investors can access insider information, which often forms the basis for continued investment decisions.

Below are two examples that will help provide greater clarity on this discussion.

1. The board Recently fired Sam Altman from the position of Open AI's CEO but had to rescind on the decision once the investors stepped in to support Sam Altman.
2. Byjus is another example where investors had representatives as board members. In fact, as per Medium (2022) quoting Y combinator resources, most of the large investors seek a board representation.

The other significant differences also arise from differences in the structure and risk of a startup as compared to a large corporation. One of the main differences results from the reporting standards. Publicly listed companies are supposed to file audited reports with the stock exchange and are subjected to intensive reporting requirements.

A startup does not need to declare results publicly. Also, what may be shared is an unverified internal financial report. This unverified information creates a large gap between people on the inside and people on the outside and poses an investment challenge. How does an investor invest when he or she cannot trust the information?

Similarly, there are other significant differences between startup and corporate finance, mainly resulting in differences in real options, incentive design, and the value to the entrepreneur. All these impact funding and highlight the need for greater transparency in startup funding. There are information asymmetries and imperfections in the market that have often been sought to be addressed by investors with direct managerial responsibilities, but as startup failures and lost investments history have taught us, these could be subjective. The interventions and decisions are at a point in time. A data-driven approach will help bring in more objectivity in decisions.

Accounting standards and recent regulations support a data driven approach. Further evidence can be found in the Accounting Standards

Like all financing transactions, there are laws related to financing of venture capital assets. Accounting Standards Codification (ASC) 820 requirements for a fair value is the main governing rule. This rule has been interpreted by International Private Equity and Venture Capital (IPEV, 2022) association that lends itself to a data-based model.

IPEV (2022) valuation guidelines highlight the need for an algorithmic model. IPEV (2022) guidelines are by the recent SEC (2023) guidelines, where even for private equity and venture capital, there is an ask for greater transparency.

IPEV (2022) valuation guidelines define fair value as " (i) Fair value should be estimated at each measurement date (each time fair value based NetAsset Value (NAV) is reported to investors (LPs)), (ii) the price of a recent investment (if deemed Fair Value) should be used to calibrate inputs to the valuation model(s), (iii) accounting standards require calibration, and

(iv) market participant perspectives should be used to estimate Fair Value at each measurement date."

IPEV (2022) guidelines that are by ASC 820 stress market calibrations as a proxy for fair value, but as Damodaran (2019) in Figure 10 explains, there may not be a comparable. One of the possible approaches then is a data model based on recent trends that indicates whether a valuation or funding decision is validated. Further need for a data model is based on the stress on understanding the market participants' perspective, which would need individual funding factors to be understood.

IPEV (2022) in its guidelines has suggested the following valuation tools:

1. Market approach
    a. Multiples
    b. Industry valuation benchmarks
    c. Available market prices
2. Income approach
    a. Discounted cash flows
3. Replacement cost approach
    a. Net assets

The price of a recent investment, if resulting from an orderly transaction, generally represents Fair Value as of the transaction date. The recent transaction price or trends is where an algorithmic approach fits in best. An algorithmic approach bases itself on the price of the recent series of investments, is based on significant factors, and accounts for benchmarks. The other methods may not fit a startup, Net present value method has been previously discussed and the replacement value method may fit only industrial projects and not software projects. Replacement value is the money that needs to be invested to create similar assets. Startups software assets may need comparable to price as they could be pre revenue and operating gains from them would be only estimates at this stage.

These methods are important. As mentioned previously, valuation is the total value of the startup assigned by the venture capitalist of which they fund a %age. The focus of this thesis is on funding. The below example explains the two concepts and also explains why we need to consider both these concepts, Funding is a more important concept for this thesis as that is linked to venture capital efficiency.

For example, a venture capitalist may assign $10M value to a company post-funding, for which they have funded $2M. As a %, their stake thus is 20%. For venture capitalists, both numbers are important.

1. Valuation as it impacts the exit returns. Suppose they settle for a high valuation early in the venture. In that case, they can risk down rounds, as mentioned earlier in the thesis, or it impacts the ability of the venture to raise further funding, thus risking its survival.
2. Funding is the amount that is invested in the startup. Many investors believe that, at least in the early stages, valuation is notional while funding is real.

In this thesis, we focus on funding.

1. As discussed in the earlier section, startup financing is like option pricing. At every funding stage, a new risk option must be calculated.
    a. The following are the factors that IPEV (2022) has stated that must be considered before a funding decision is made. These include.
        i. The stage of development of the Enterprise changes (from pre-revenue to revenue to earnings).

ii. New markets develop.

iii. New information becomes available.

iv. Information previously used is no longer available.

v. Market conditions change.

The factors lend themselves to an algorithmic approach suggested in this thesis.

2. Funding is real dollars spent to grow the business. In a case mentioned in the later section of this thesis, funding is a discrete number, and the negotiation is generally around the percentage of the startup it accounts for. For example, if a startup founder needs US$2 million to scale a business, his view may be that US$ 2 million is at a final valuation of US$ 20 million. In contrast, an investor may agree to fund US$ 2 million but at a US$ 15 million valuation.
    a. In both cases, the funding amount was the same, US$ 2 million. This amount will usually be backed by detailed planned expense sheets that will tie back to the US$ 2 million.

Thus, in this thesis, an algorithmic approach is used for funding levels based on the advice of IPEV (2022) guidelines. IPEV guidelines fit for funding levels, and funding is the theme of this thesis, i.e., the objective is to ensure the profitability and efficiency of the venture capital.

Securities and Exchange Commission (SEC,2023) has also recently updated its governance requirement for private equity and venture capital. The new rules are structured around better explainability of the funding decision. The intent is to drive transparency with the limited partners (LP's) as well as restrain some of the practices that gave an unfair advantage to few.

A summary of some of the guidance is in Table 14 below.

In Table 14, with the areas impacting venture capital funds highlighted.

Table 14 – Implications of the new SEC rules on the venture capital funds (key ones where the thesis will fit)

<table>
<tr><th rowspan="2">Rules</th><th rowspan="2">Description</th><th colspan="2">Apply to</th><th rowspan="2">Applicable from</th></tr>
<tr><th>Registered funds</th><th>All other advisors</th></tr>
<tr><td>Preferential Treatment</td><td>Prohibits advisors from granting preferential treatment and redemption rights that would have a negative impact on the other portfolio investors</td><td>Yes</td><td>Yes</td><td>>US$1.5 Bn – 12 months

<US$ 1.5 Bn – 18 months</td></tr>
<tr><td>Restricted activities</td><td>Restricts advisers from engaging in certain activities, including (among others) charging or allocating certain fees and expenses to private funds, unless the adviser meets certain disclosure requirements</td><td>Yes</td><td>Yes</td><td>>US$1.5 Bn – 12 months

<US$ 1.5 Bn – 18 months</td></tr>
<tr><td>Quarterly Statements</td><td>Requires SEC-registered advisers to provide investors with quarterly information about private fund adviser compensation, fund fees and expenses, and performance.</td><td>Yes</td><td></td><td>18 months</td></tr>
<tr><td>Advisor led secondaries</td><td>Requires SEC-registered advisers that engage in adviser-led secondary transactions:
• to obtain and distribute a fairness or valuation opinion</td><td>Yes</td><td></td><td>>US$1.5 Bn – 12 months

<US$ 1.5 Bn – 18 months</td></tr>
</table>

The recent changes in market sentiment, losses being seen by the venture capital, and now the regulatory changes, are all pointing towards the same direction that there is a need for a greater transparency in valuation and funding. Also, the IPEV (2022) guideline are indicating that a comparable method may be better.

Comparable methods are based on a data-based approach.

In this thesis, the stress is on factors that could influence funding. At the same time, many factors could affect a VC's decision to understand the market and hence fund. The set of factors were scrubbed from previous literature and the following factors were considered. These included (i) firm size measured as number of employees, (ii) lead investors, (iii) market size, (iv) technology risk, (v) signals, (vi) patents, and (vii) trademarks.

In this thesis, multiple data models are run with a selection of these factors to identify the right factors for the right situation. Some additional factors have also been considered but not mentioned in the above list as no historical research was identified that supports it either from an investee or from an investor. The factor was not something that would either send a signal to a venture capital to fund, nor was it a factor that would lead to higher returns for a venture capital.

We review individual factors and the academic theory that either supports the importance of a factor or indicates that a part of it could be significant.

Funding factors

Firm size is measured as the number of employees.

In this thesis, it is argued that the number of employees should influence a venture capitals decision for follow-on funding as well as survivability of the startup. While initial funding focus had indicated that the founder's profile and the startup team profile would be a key funding consideration (Kaplan et.al., 2009; Ewens and Marx, 2017), from a venture capital return perspective, the number of employees seem to be more significant. Previous research indicates as to why the number of employees could be important.

The argument is based on several factors, including the ability to attract talent, which signals the strength of the startup and its high technology impact. The size of a startup influences its learning ability. More than anything else, the number of employees indicates the founding team's ability to communicate their vision to prospective employees. Moreover, later in the thesis, we cover a concept of valley of death that will apply to startups that are unable to scale. For a venture capitalist, inability to scale is where they lose their investment. Another interesting concept is that today the employees have options.

Today, employees have options and alternatives. A high number of employees in a startup is effectively communicating that people are willing to bet on the startup, i.e., a startup has funds to pay salaries, and employees who may have conducted pre-employment research have found the startup may have a potential to survive and thrive. That is the reason we expect this factor to be significant. Recent research from Esen et al. (2023) suggests that high-quality employees influence the startup's funding ability.

Employees' preference for large employers can be found in the traditional theory of ability sorting. The traditional theory of ability sorting strongly suggests that high-ability workers choose jobs with well-established firms. Sorting, when combined with Human Capital Theory, enables us to arrive at this conclusion (Weiss, 1995). Broadly, a better job with a larger company was suggested as a way of signaling talent by employees. Based on this theory, it would be assumed that the startups may be unable to help attract the best talent, at least not in the required numbers. A startup must be unique to attract good-quality employees.

Roach and Saumermann (2023) offer an alternative theory after an empirical study of 2,394 science and engineering PhDs from graduate school. As per Roach and Saumermann (2023), some startups offer other nonpecuniary benefits that can attract highly qualified talent. Nevertheless, for a startup to offer these nonpecuniary benefits, it must offer empowerment, an opportunity to work on new technology skills or a prospect of long-term growth. By that standard, we expect the employees in startups to be younger. These non-pecuniary benefits and work with high technology skills are some of the cues that a venture capitalist should be on the lookout for.

The fact that startup employees tend to be younger aligns with the previous research. Ouimet and Zarutskie (2010) identified a disproportionate percentage of younger startup employees. They argue that the younger employees seek work aligned with the new technology skills they have learned and are willing to take more significant risks if they think the startup is more likely to survive and thrive.

The theory is supported by research of Oiumet and Zaustskie (2010). Startups are considered fast-growth entities if they survive (Ouimet & Zarutskie, 2010) and hence would attract talent willing to accept higher risk in the hope of long-term returns. Roach and Saumermann (2023) state that startups offer 17% less pay than large corporations. The benefits of working for a startup include autonomous structures, newer technologies, and faster growth. All these require the startup to survive and grow. So, the number of employees is a surrogate for new, monetizable technology.

Previous research, especially the recent research from Esen et al. (2023), suggests that venture capital considers the non-founding employees while funding. Historically (Beckman et al., 2007; Bertoni et al., 2011; Plummer et al., 2016) have all suggested that venture capital only considers the founding team and their experience for the funding decision. In this context, a broadening of the number of employees must be explained.

The number of employees may be a critical factor for follow-up funding, and not necessarily for the first round of funding. Founding members and their experience will be more critical for the first round of funding and will be covered later in this thesis. Later, in this thesis, we have a case of new startups receiving the first funding. This case explains why the number of employees may not be a determining factor.

The case is different for a funded startup. Funded startups have an initial business case that venture capital has validated. In addition, with the ability to offer salaries, and not just equity, the employees can evaluate the startup and decide whether they want to join it. More employees would then imply more positive validations. For similar business areas, an ability to attract a larger team means that more employees expect the startup to survive and grow. From a venture capital perspective, this is an additional point of validation.

There is also a need to scale up and scaling up requires people. As Jansen et.al. (2023) indicated in their recent research, scaling up requires the same process or product to be replicated across geographies or product groups, and that requires people.

Hence, we come to the first hypothesis that we want to test in this thesis:

H_1 – For similar industry segments, the number of employees will be a significant factor in the follow-on funding.

The hypothesis will be tested with a dataset of active startups that have been previously funded and are seeking further funding rounds. The same industry sector will be used as a control variable. Table 15 contains a summary of the discussion.

Table 15- Summary of employee size discussions.

Discussion area	Main discussion
Previous research	Initial focus has been on founding team qualification. Also, historical research has argued that employees would prefer large corporates as signals for their talent. Some recent research has indicated that startups can be considered contextual by new professionals, and they may want to work in these.
Gap being tested	The focus has been on qualification of employees but never on the fact that an ability to attract employees is a positive validation of the startup and should provide confidence to the venture capitalist that the startup can scale.
Segment being tested	Impact of size of company on investment assurance for follow on funding is being tested.
Expected conclusion if analysis failed to reject the hypothesis	The argument in this section is based on two facts (i) startups need high quality employees and founders, and (ii) there is a need for idea to be scaled for venture capitalists' investment protection. Scaled ideas can lead to an exit. In this section, we test (ii)

Lead investors

A lead investor (or lead) is the first to commit to a given round of funding and agrees to set the terms for any other investors participating in the financing. This is called "leading the round." The lead investor generally makes the largest investment in the round and usually takes a board seat as part of the deal (Sparks, 2023).

In private equity, the role of a lead investor is like an underwriter. They are usually the first to estimate the venture's risk and conduct due diligence. A branded lead investor usually provides an increased surety for an investor, generally referred to as a follow-on investor that follows a large investor's lead and invests based on their underwriting. A few points need to be noted.

1. A lead investor may vary by funding round. Usually, the venture capital that led the previous funding round is offered an opportunity to lead the next round.
2. A historically branded lead investor usually implies that the startup was good at one stage. Whether it will still apply is still being determined. IPEV (2022) states that new information necessitates new underwriting. In this context, the branding of a historical lead investor may not apply. As an example, Y Combinator is one of the best accelerator brands in the world. However, even there, 93% of the startups either fail to raise the right amount, are sold for amounts less than the required returns, or fail to generate the proper revenues (Blodget, 2013).
3. Despite its limitations, a good lead investor, or any lead investor, may assure other investors. The startup was thoroughly vetted at a stage and found to be a good investment.

Lead investors take different forms. These are usually the incubators, accelerators, or crowdfunding syndicates for the first round of funding. Some of the accelerators, such as the Y combinator, are very well known and are known to drive funding. Some accelerators fund the first round against a prescribed equity percentage. This thesis has included an example where startup funding was decided for a Mid-Western US accelerator.

For early-stage startups, this is often an association with marquee investors, and for late-stage startups, it is the association with investment banks or private equity firms that can help with an exit either as an IPO or as an M&A deal. It is often believed that association with a top lead investor can help attract funding. For example, Facebook's initial funding was from Peter Theil, a well-known individual investor. Similarly, association with Microsoft has helped OpenAI become a valuable company.

Theoretically, the case for lead investors is often built around signaling theory (Ahlers et al., 2015). The examples of Facebook and OpenAI help to validate the role of signaling derived from association with top investors. The case for signaling is built on two dimensions: information asymmetry and investor sophistication. Different investors have different sophistication. Venture capitalists are sophisticated investors with the financial acumen to evaluate a proposal. In contrast, retail investors, especially under crowdsourcing, may need to be savvier and may need external signals for validation.

Leland and Pyle (1977) highlight the need for due diligence before investing in a startup. Not all investors have the sophistication for complete due diligence, and there is a related cost to conduct risk due diligence. Some authors have also noted (Ahlers et al., 2015) that the cost of due diligence is significantly lower for sophisticated investors, such as venture capital, compared to less sophisticated investors, such as crowdfunding syndicates.

In this context, two arguments are usually made: (i) since retail investors lack the sophistication to validate the investment information, a lead investor may be an external source of validation that will signal an enterprise investment worthiness, and (ii) lead investors create information asymmetry and are usually accompanied with disproportionate benefits like a board seat so that it may be counterproductive to the investors. Overall, the verdict is that lead investors or syndicates may help from a crowdfunding perspective.

Zhang et al. (2023) have argued the first case from a crowdfunding perspective, where their argument based on a study of 179 lead investors from AngelList is that the lead investors' integrity and ability favorably impact the fundraising efforts. This study is US-specific and uses signaling theory as a basis.

To define signaling, Connelly et al. (2010) define signaling theory as related primarily to decreasing information asymmetry and creating legitimacy for an offering where information sources are limited. One of the examples provided by Connelly et al. (2010) is of a company that recruits a high-potential board before an IPO. Zhang et al. (2023) base their arguments on similar logic and say that retail investors may need to be savvier for complete due diligence. Zhang et al. (2023) state, “Therefore, lead investors act as third-party affiliations and are essentially a substitute for the signals of entrepreneurs.”

The focus of this thesis is on venture capital and not on individual retail crowdfunding investors. The second argument of agency costs and disproportionate benefits to lead investors may be more relevant to the thesis. The basic premise of agency theory is that both principals and agents are assumed to be rational economic-maximizing individuals. Therefore, the separation of ownership and control will result in decisions by the agent that are only sometimes in the principal’s best interest, and costs (agency costs) will arise to bring the agent’s behavior into line (Landstrom, 1993). For retail investors, one main reason for this is that “trustworthiness” is especially crucial in equity crowdfunding, and lead investors are usually more trustworthy than entrepreneurs in inexperienced investors’ minds (Li et al., 2020). The question, in the case of a VC-funded startup, is how you classify lead investors.

Chen & Ma (2023) raise exciting perspectives in this aspect that validate the debate made earlier. As per Chen & Ma (2023), the lead investors may be considered as “insiders,” have differential access to information, and may be receiving preferential pricing. The same views are echoed by Mnuchin & Phillips (2017) in their US Government of Treasury report, where they also state that even for crowdfunding, lead investors and crowd investors have misaligned goals. While performing due diligence, the lead investors obtain an information advantage, which can allow them to exploit the crowd's interest.

How does this affect the usual retail or venture capital investors that take the lead from named or lead investors? For retail investors, lead investors matter; this may not be true for venture capital. Hochberg et al. (2007) and similar research have indicated that lead investors are a model for venture capital where they prefer to co-invest. Co-invest is mainly because smaller venture capitalists may not have the team to conduct full due diligence and may outsource some tasks to lead investors.

Clayton (2020) also suggests that "large investors commonly use their bargaining power to negotiate for individualized benefits outside of fund agreements, where the benefit of the bargain is not shared with other investors in the fund." The agency cost related to lead investors in a venture capital deal is expected to be significant. Han (2006) indicates that lead investors may be considered as inside investments, and typically, there is a U-shaped relationship between the percentage of inside investment and other investor returns. Han (2006) has contextualized that any inside ownership above 25 percent would reduce benefits for other investors simply due to principal-agency conflict.

This thesis argues that the number of lead investors is not a significant determining factor when deciding on further funding. The argument is that once a startup has been initially funded, it is credible, and that venture capitalist will fund either based on their own due diligence or will be a part of a syndicate that funds the startup. So, by increasing the number of lead investors, the entrepreneur may not be improving the probability of getting follow-up on funding. For the venture capitalist, it may not add any additional information that may provide a funding lever. Hence, this factor is not being considered in the thesis as an important factor to test. There are multiple reasons for not testing this as a hypothesis based on the literature review. Some of these are:

1. With updated SEC (2023) rules, it will be interesting to note how lead investor concept evolves. Usually, lead investors have access to preferential rights. New SEC (2023) rules restrict a preferential treatment. SEC (2023) rules “prohibits advisors from granting preferential treatment and redemption rights that would have a negative impact on the other portfolio investors”.
2. Lead investors may vary by deal. There are some early-stage investors, and some venture capitalists focus only on late-stage investments. As a startup moves between stages, it will need to find a new lead investor. A new lead investor usually conducts its own due diligence; hence the number of lead investors should not be significant at this stage.
3. Based on practical experience, even in a co-lead or follower scenario where the venture capital is investigating as a part of a syndicate, it does conduct its own due diligence. The only advantage of a lead investor for a follow-on investment is that it helps a startup be considered by other members of the lead investors syndicate, and that may help the startup to get funded. It does not alter a venture capitalists’ risk and does not increase their investment efficiency.

Market Size

The end objective of any investor is to seek high returns for their investment. As argued earlier in this thesis, returns depend on exit, either through a public market offering such as an initial public offering (IPO) or through mergers and acquisitions. Exit, in turn, is dependent on several factors. These include (i) the growth trajectory or the ability of the startup to continue generating profits, (ii) unique IP the startup has developed that could be valuable for an acquirer, and it may allow the startup to acquire the technology, and (iii) an offering gap for an acquirer in their current product or servicing. The acquisition, in this case, helps complete the product portfolio. A few examples help to elucidate these different strategies.

- Instacart is a 2023 example of a technology startup that exited through an initial public offering (IPO). The shares are now traded on NASDAQ, and venture capital investors can trade the shares to record gains.
- Google acquired Android in 2005 to enter the mobile operating system market. Android is an example of technology being unique and valued by the acquiring company. The acquirer believes it can create a new market with the acquired technology.
- A last example is Avaloq, which was acquired by NEC in 2022. NEC operates in the banking software market, while Avaloq is a specialized private banking software. After the acquisition, NEC planned to introduce Avaloq to the Japanese market in 2024.

Specific to market size, growth trajectory, or the ability to grow revenues would depend on the market size. Antler (2022), a large early-stage accelerator, has stated it as a part of their requirement to be included in a founder's submission for initial screening. That is because early-stage startups may still have to test the product market fit and "pivot". "Pivot" is a startup term that means that a startup may change its offering if the initial planned MVP does not have a significant market demand. Ability to "pivot" depends on the market size and could be significant for the investors returns. A few examples why this is important are listed below:

1. Slack that is a US$ 16 Billion company, started as a gaming startup. Slack was the internal communication tool developed. Today, Slack is a communications company that is no longer into gaming.

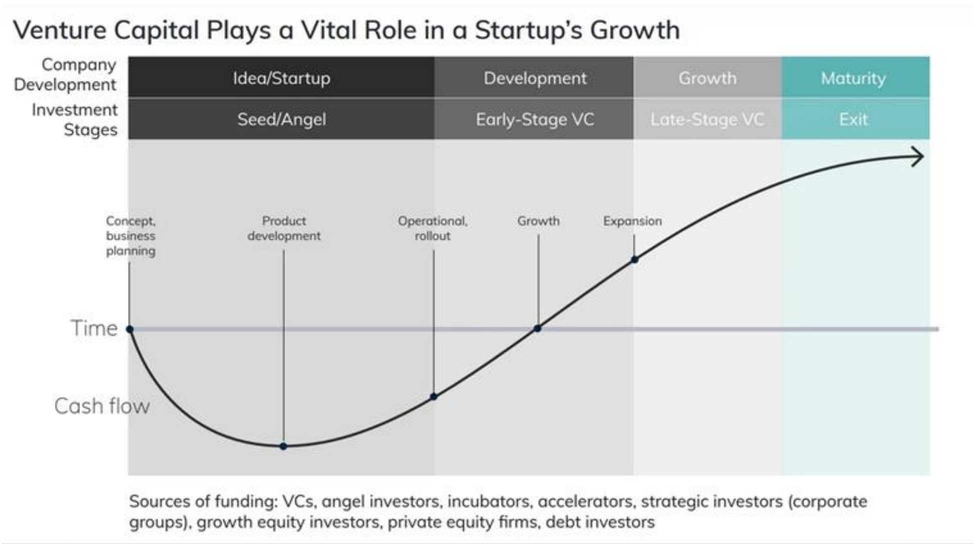
2. YouTube started as a site where people could create a video describing themselves to their ideal partner profile.
3. Twitter was originally a podcast site in direct competition to iTunes.

In each of these cases, the market size was large enough to support a "pivot", a change of business model.

For startups, there are three types of market sizes. Antler (2022) and other early-stage investors define the market size as total addressable market (TAM), service addressable market (SAM) – the percentage of the market that the startup's products or offerings serve, and service obtainable market (SOM) – the actual amount of market that is being served by the startup's products or services. Differences between SAM and SOM could be the focused segment (as against the population) or the geography of operation. Most accelerators and early-stage investors interviewed will insist on a high TAM at a minimum. While the market size is important for early-stage investors, will the same apply to venture capital investors? The answer lies in what venture capital investors price in their decision-making process.

In their seminal paper, Gompers et al. (2016) suggest that venture capital, as investors, tends to be inconsistent with the finance theory. They suggest that most venture capital discounts idiosyncratic risk and does not discount the market risk. Gompers et al. (2016), in a study of 689 venture capital finds, found that none of the business-related factors—business model, technology, market size, and industry—was rated most important by more than 10% of the venture capitals for success or failure. Richard (1999), in an IMF paper, defines idiosyncratic risk as risk that is endemic to the asset class, industry in this case.

To some extent, the reader may question the findings of Gompers et al. (2016) as all the usually critical factors, such as business model, technology, market size, and industry, are important. If these are different from the North Star metrics, what would convince the investors that the startup is worth investing in? If we go back to the original discussion and thought process where the investors seek an exit, it is easy to understand as to why the market size may not be that important. Figure 11 (included below for reference) indicates that venture capitalists' investment is in the operational rollout, growth, and expansion phase. The MVP should have been proven for the startup to be venture capital funded.



So, what would ensure that the venture capitalists are able to generate a return. The answer to this question lies in product-market fit (PMF). Table 16 details product market fit and why it may be more important for venture capital.

Figure 16 – Product market fit

Factors	Zero product market fit	Some product market fit	High product market fit
Qualitative indicators	• Customer confusion/ indifference. • Difficulty defining customer persona. • Long sales cycle often without closing.	• Initial testimonials and case studies. • Defined persona with repeatable use cases. • More predictable sales cycle with more closing.	• Strong customer advocacy with referrals. • Clear value in customer workflows. • Short sales cycles / high conversion rates.
Quantitative indicators	• Stagnant / declining monthly recurring revenue. • High customer acquisition cost v/s the customer lifetime value • Small sales pipeline • High churn rate (>5%) • Low/negative NPS	• Growing monthly recurring revenue. • Balancing customer acquisition cost and the customer lifetime value • Increasing qualified leads • Moderate churn rate (2-5%) • Positive NPS	• Predictable monthly recurring revenue growth. • Customer lifetime value exceeds customer acquisition cost. • Robust sales pipeline • Low churn rate (<2%) • High NPS
Revenue indicators	• Sporadic revenue from one-time projects or deals	• Initial recurring revenue streams • Revenue growth observed but not consistent	• Consistent revenue growth • Significant recurring revenue, • Revenue expansion from existing customers.

Source: Salfati (2023)

Based on these facts, market size should not be a consideration for venture capital, yet this has been considered for some of the data models within this thesis. In our thesis, we have identified that market size matters for initial/first investment, angel investments, and the survivability of industries where the business model has not been proven to date. These findings are in line with the initial discussion in this section.

Market size and angel investors must be covered in this thesis. As the introduction mentions, the thesis starts with the paradigm that ventures capital helps build innovation and economic growth and that startups are best suited to drive innovation. Angel investors are usually the first funding a startup receives, which is central to the startup life cycle. First funding is the stage where technology moves beyond proof of concept to the first commercial test.

Angel investors matter in the initial stages of funding; angel investors are endogenous to the venture capital investment process (Dutta & Folta, 2016). Liu

(2020), in a paper published by the Bank of International Settlements (World Bank), defines angel investors as wealthy individuals who invest their wealth in early-stage firms. They usually invest before the venture capital funds and are known for providing their professional and business skills in addition to funding.

As noted earlier, only some startups succeed, and usually, venture capital can realize the returns only on exit. Also, as mentioned in Figure 11 earlier, cash flows for a startup turn positive in the early-stage growth phase, usually at the first venture capital funding stage. The question then is what gives an angel investor or venture capitalist confidence that the startup can pivot to growth. That is where market size is expected to play a role as demonstrated in the example of Antler.

The importance of market size for an angel investor has been stressed by Maxwell et al. (2011). Maxwell et al. (2011) collated the previous entrepreneurial literature on angel investing and interviewed 150 angel investors. Nine of the thirteen previous literature Maxwell et al. (2011) evaluated mentioned the importance of market size for angel investors.

Few other studies are critical for an overall understanding of the importance of market size for early-stage investing. Sato and Yamamoto (2012), in their study for The Research Institute of Economy, Trade, and Industry, Japan, found a correlation between the population in the prefecture and the number of entrepreneurs. Prefectures in Japan are regional authorities comprising municipalities and broader regional administration. Sato and Yamomoto (2012) found that an increase in population density by 10% leads to an increase in entrepreneurs by 1%. Population density is assumed to be the surrogate for market size.

Sato and Yamomoto (2012) also found that the relationship was nonlinear, i.e., certain prefectures with high population density had lower-than-expected entrepreneurial activity. For this, the work of Sato and Yamomoto (2012) needs to be combined with a paper produced by Hellmann and Thiele (2014) for the National Bureau of Economic Research.

Hellmann and Thiele (2014) correlated the market size with entrepreneurs' incentives and the entrepreneur's supply. As per Hellmann and Thiele (2014), if the entrepreneur's incentive is significant, their supply is inelastic, and there is little urgency, the market size effect on angel investors is insignificant. Here, we are assuming that there is urgency for the investors.

Hellmann and Thiele's NBER theory (2014) also explains why market size is important for angel investors rather than for venture capital. It is known that angel investors are largely individuals who also invest due to interest in the industry Maxwell et al. (2011). The interest in the industry and the personal relations that they can establish create a sense of urgency. Market size is an important metric for them as it creates a sense of urgency. In the startup world, it is termed FOMO, or fear of missing out.

On the other hand, venture capital enters late in the investment cycle, so it has the advantage of proven traction. One of the investors told me recently in a panel, "There is real money for real solutions. You give me a startup with real traction, and we have a cheque ready" (Kakar, 2023). Based on the research, we can state:

H_2 – The market size will be a significant decision factor for first funding.

H_3 – Greater market size will be a key feature for startups in business areas where the business model is under development.

H_3 is often overlooked but may be an important case to consider. For a relatively new business segment such as sustainable development where alternatives exist, the venture capitalist may consider market size. If we go back to the three market sizes defined in earlier in the thesis:

1. TAM – Total addressable market.

2. SAM – Serviceable achievable market

3. SOM – Serviceable obtainable market.

For a new business segment, based on interviews with sustainability investors, SAM and SOM are difficult to estimate. While this was mentioned in various meetings with investors, there is no previous research or data that can help establish the importance of a large TAM, or for the matter market growth rates, importance for these sectors. The thesis attempts to take the first step towards the correlation between these factors and sustainability segments survivability. Could this be the idiosyncratic risk that affects venture capital investment in such sub sectors (Gompers et al., 2016). Summary of the discussions are enclosed in Table 17 below.

Table 17- Summary of market size discussions.

Discussion area	Main discussion
Previous research	• All accelerators and incubators usually insist on TAM (Total addressable market) to be included in the pitch submission. • Many scholars have identified market size as a significant factor driving angel investors investment decisions. • Venture capitalist discount the idiosyncratic risk and not the market risk.
Gap being tested	• The relationship between market size and angel investors has been derived based on interviews and not through a data driven approach. Also, the approach has to be tested for the current negative sentiment market. • Does market size help a venture capitalist estimate idiosyncratic risk for a new segment?
Segment being tested	• First funding • Survivability
Expected conclusion if analysis failed to reject the hypothesis	• For first funding, in a negative sentiment market, scalability may be secondary to other investor considerations. • Market size could be a mitigant to idiosyncratic risk for some segments.

Technology

Risk management is central to a high-technology startup. Most startups, by definition have a higher risk than organized sector. The risk results from using untested technologies that the organized sector will not invest in due to the high risk that they carry (Roca & O'Sullivan, 2022). For the technology startups being considered in this thesis, most of the risks are associated with technology development, application or lack of application control. These could be.

1. Consumer experience – Startups often experiment with new customer journeys and user experience. Since there may be no precedent for this experience, customers may prefer the earlier experience or be unable to differentiate between the current and new experience. Since consumers cannot perceive a difference in both cases, they may not adopt the startup processes. This is an example of technology application not being accepted by the customers.
2. Credit risk – Startups, especially in the fintech and data spaces, tend to deploy new databases and algorithms; these algorithms need to be tested. Untested algorithms may lead to three different risk conditions. (i) the datasets may be insufficient or lack the parameters and scenarios to train the algorithms, leading to a case where the algorithm may be inefficient in some scenarios (ii) the data may have bias, and the bias may reflect in the results, and (iii) the scenario may require longitudinal data. The business case may need data over the years, and that scenario may be challenging to simulate.
3. Compliance risk – Unlike a bank or a large corporation, startups may not have full compliance support and may not be aware of all the regulations. They may violate some regulations and be subject to Government penalties or sanctions.

However, on the other hand, technology is also central to these startups and is the main differentiator. Given the duality of technology as the main value driver for a startup as well as a potential risk to its survival, the thesis explores two aspects of technology development and its application. These are: (i) does innovative technology and technology development help in valuation and, therefore, leading to improvements in efficient venture capital fund deployment, and (ii) does innovation create a risk for the survivability of a startup? If yes, in what conditions. In this thesis, we have explored both these factors using data models. However, one thing to state upfront is that high technology is required for the startups considered in this thesis and a driver for their investor attractiveness as has been mentioned in historical literature.

Emir Hidayat et al. (2022) and Hyytinen et al. (2015) have summarized the previous research that innovation increases the attractiveness of a startup. The argument was originally made by Schumpeter (1934). Emir Hidayat et al. (2022) and Hyytinen et al. (2015) have also stressed on the duality by stating that innovation is introducing a new process or technology, which would normally be a higher risk than existing corporate processes.

The risk associated with these startups has been very well captured by Teberga et al. (2018): “Software startups are companies with no operating history, no business model and no market share to defend, but with fast growth, and focused on the production of cutting-edge technologies.” Broadly, it is a risk to the startup due to untested technology that is either unable to deliver the promised value, fails to be fair and free of bias that can be tested over a longer period, fails the regulation, or even cannot be commercialized.

The argument in this section will be based on the attractiveness of technology for a VC, the technology readiness level, the link between technology and business models, and finally, the regulatory impact of what is termed the “valley of death”.

Attractiveness of technology for a VC

The role of a venture capital fund manager is to maximize the returns. Investing in risky high-technology startups usually provides the best returns. As discussed earlier in this thesis, high technology leads to innovation and productivity gains, which drive economic growth. As stated earlier in the thesis, the same was also mentioned by Kerr et al. (2014) findings that VC is attracted to “capital-efficient “sectors for experimentation and subsequent scaling up. Metrick and Yasuda (2021) had also mentioned this in the context of the development of the venture capital industry in the US. There is also other theoretical evidence that supports this.

Hyytinen et al. (2015) argue that high technology can lead to new platforms, categories, or products enabling market entry. Schumpeter (1934) argued that technology leads to market power and, hence, greater acceptance of the product or services. Porter (1980) had argued that technology leads to competitive difference. The positive aspects of new technology combined with the work of Samuelson & Davidson (2008) that suggests innovation leads to riskier, more complicated, and less linear startup processes fit well with this innovation with the funding based on the venture capital model detailed earlier in this thesis.

The operating phase for venture capital investing in a technology-driven startup is the possibility of nonlinear growth. In practice, venture capitalists invest in hyper-scaling startups. Only startups with a possibility of exponential growth fit the venture capitalist’s business model. As discussed in the earlier sections of this thesis, venture capital invests for 3-5 years, after which they seek an exit. Exit usually requires the startup to be revenue positive. The startup needs to demonstrate an exponential growth rate to become revenue-positive and reach an exit valuation. Both research and recent corporate history prove that such growth is usually associated with high-tech startups (Davidson & Vaast, 2010).

The nonlinear growth prospects lead venture capital to invest in and provide better funding for high-technology startups. Venture capital can absorb the risk of failures based on their assessment of the technology and its commercialization leading to better efficiency in funds deployment. As stated earlier in the thesis and based on the historical venture capital returns data, the venture capital returns are not normal and are highly skewed towards startup failure. Few of the startups need to generate supranormal profits for overall returns at a portfolio level. Supranormal profits require an exponential growth, and that is what venture capitalist target in their funding process. The question would then arise as to how do venture capitalist evaluate high technology.

High technology is usually evaluated by venture capital through their experts, through patents, or the funds allocated for technology development. In this thesis, we will cover the aspects of funds allocated for technology development using the applications built as a surrogate. Patents are a complete topic and key to the overall objective of this thesis, drive towards innovation and venture capital as a support structure enabling that innovation. Patents would be covered separately.

Some of the questions in this context would be:

1. Practically, as mentioned earlier, venture capital focus on narrow segments such as artificial intelligence and geographical areas such as Singapore and Indonesia. In the context of this super specialization, does technology investment really make a difference? Or should the difference originate more from high

technology indicators such as patents? Baron et al. (2018) have argued that R&D intensity varies within standard sectors and while there is some heterogeneity within a sector, it may not be sufficient. They also mentioned that a firm's patent position significantly increases the pressure on a firm to invest in R&D.

2. Given that the focus of the thesis is on venture capital fund deployment efficiency and that needs commercialization focus, should startups and venture capital funds be bothered by the number of applications developed, or is there an optimal mix of fund deployment that they should be considering? Previous research has indicated that between 5-15% of the budgets need to be spent on R&D (Shanthi, 2022).

Given the perceived importance of technology for venture capital, we still want to confirm whether increased technology investments lead to better funding and funding returns. As mentioned by Baron et al. (2018), better technology within the sector can either be demonstrated by patents or technology spends. With the number of applications as the only available surrogate, the thesis hypothesizes.

H_4 – The number of software applications a startup develops will be positively correlated with VC funding raised.

But as discussed earlier, technology also leads to a risk. The next discussion aspect will be on whether technology risk can threaten a startup's survival.

Innovation as a potential risk for startups survival

There is a reason that large corporations refrain from investing in untested technologies. The untested technologies are significantly riskier than proven technologies (Roca & O'Sullivan, 2022). The argument for this risk is based on technology readiness level, the relationship between technology and business model, and crossing the "valley of death."

To be commercialized and to scale, technology needs to find its product-market fit, and that may require a significant number of experiments. The best example of closeness to commercial life is in the technology readiness level framework developed by NASA (1970) to evaluate technology readiness for flights. While the model was for space exploration, its principles and rigors can fit the corporate and startup world. However, startups normally grow by launching multiple MVPs (minimum viable products). The guide is detailed in Figure 18 below.

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Figure 18 – Technology readiness level

Technology Readiness Level	Description
9	Actual system “flight proven” through successful mission operations
8	The actual system was completed and “qualified” through tests and demonstration
7	System prototype demonstration in the space environment
6	System/sub-system model or prototype demonstration in a relevant environment
5	Component and breadboard validation in a relevant environment
4	Component and/or breadboard validation in a laboratory environment
3	Analytical and experimental critical function and characteristic proof of concept
2	Technology concept and application formulated
1	Basic principles observed and reported

Source: NASA (2023)

Goji et al. (2020) applied the technology readiness level methodology to startups with stark observations. Patents in Goji et al.’s (2020) evaluation are classified as technology readiness level 2. For many technology sectors, such as biopharmaceuticals, investors start engaging at technology readiness level 2. For other sectors, such as AI and sustainability, the engagement is usually at technology readiness level 3.

The framework provides a visual and a framework on the risk apparent in a technology startup. For technology to mature, it needs to be at technology readiness level 9, while the investments are at stage 2 or 3. While the growth can be nonlinear as technology readiness matures (Samuelson & Davidson, 2008), the risk will be apparent since technology is early in its maturity cycle. For the technology to mature, the technology must be managed through a correct business model (Chammassian & Sabatier, 2020).

Chammassian and Sabatier (2020) built on the logic of Furnari's (2015) that built a logic that technology startups succeed due to their ability to convert the technology solution into a revenue generation business. As per Chammassian and Sabatier (2020), consumers of technology expect improved experiences and additional services rather than pure product consumption, which is called servitization. Commercialization is much more difficult in the context of high-technology startups and, hence, a risk to their survivability.

These risks are termed valleys of death in the context of technology-driven startups. The Valley of Death (Roca & O'Sullivan, 2022) is usually understood as a phase in the maturity of an emerging technology after funding the proof of technology or proof of concept and before the market is willing to accept the level of uncertainty associated with proprietary application development and scale-up. Valley of death also becomes extremely critical where regulatory rules are developing, as is the case with both the sectors considered in this thesis – artificial intelligence and sustainability.

Initially, in our thesis, it was mentioned that sustainability is one of the key focus sectors. Sustainability was chosen for three reasons. (i) As mentioned earlier, cleantech saw the highest venture capital investments in 2023. The focus of the thesis is to improve venture capital funding and hence the sector with the maximum funding has to be considered. (ii) it is an important sector with much focus. Most governments are concerned about the impact of climate change and heating, so it is important to find the right model and factors that could influence venture capital funding, and (iii) it is a sector that is high risk due to unproven technology, business model risk, and evolving regulations. Startup survival is a key risk in this sector. Hence, we will test these two hypotheses in this study.

H_5 – In a new industry, the previous founder's professional experience may be significant in developing a profitable business model.

H_{76} – As risk increases, so does the probability of a startup failure.

For H_6, the risk involved in a startup would be categorized into ecosystem changes and non-ecosystem changes. An ecosystem change is like electrical battery charging networks for electronic cars. Risk in this context would be the cross product of ecosystem change and willingness to invest. For each of the startup considered in this segment, qualitative research was conducted to arrive at this risk category. The summary of findings and discussions are in Table 19 below.

Table 19- Summary of technology findings.

Discussion area	Main discussion
Previous research	• Startups as a definition within this thesis, invest in high technology solutions to hyperscale the business. • Technology scalability is an important criterion for venture capitalist to invest. • At the stage of venture capital investment, the technology is not ready for commercialization. • Commercialization is required to protect the venture capitalists returns and to convert startup into a successful organization.
Gap being tested	• In a standard industry segment such as artificial intelligence, it is not enough to invest in technology but to create differentiation. Differentiation will be tested as a part of the patents testing. • Technology introduction may create ecosystem risks, and it is important that these risks be addressed to protect venture capital investments.
Segment being tested	• Follow on funding. • Survivability
Expected conclusion if analysis failed to reject the hypothesis	• For high technology startups, differentiation in technology would help with funding efficiency. • If the segment is on focus, i.e., such as sustainability, the ecosystem risks would need to be resolved.

Signals

Signals are important both from a startup's perspective and for a venture capital funding efficiency perspective, Startups have limited historical and operational data, increasing the fundraising challenge. To raise funds, startups, and their founders need to create a differentiation enabling venture capital funding. Without operational or historical data, the startups can rely on cues or signals to build their case. As discussed earlier in this thesis, signaling theory is one of the tools that founders and startups can deploy to differentiate themselves. For a venture capitalist who needs to evaluate thousands of proposals, signals provide a screening process.

The startups in press are also validated independently, hence should have a better probability of returns (Conti et al., 2011). While the importance of signals from a startup's perspective has been studied significantly, its impact on venture capital returns and efficiency has largely been a gap except for the work of Conti et al. (2011) which also focuses more on startups value.

To understand the importance of signals and the impact that they may have on funding, this section of the thesis will develop the concept of signaling theory and its importance, build on the concepts of the use of signals for markets, and its importance for startups.

Signaling theory describes the behaviors of individuals or organizations when there is an information asymmetry (Connelly et al., 2010), a typical case for startup funding. Entrepreneurs have access to more information than venture capitalists have.

Individuals and corporations make decisions based on freely available public and private information that may be available only to founders (Connelly et al., 2010). Venture capitalists can make better decisions if private information is available. The challenge for a startup arises as the private information needs to have credibility due to a lack of historical and operational data. Signals are surrogates that fit this role and are largely through association with other credible sources such as board composition, media coverage, or educational and professional credibility (Plummer et al., 2016)

Four cases are considered in this section (i) the use of signals to attract venture capital funds for an early-stage startup, (ii) the use of grants as signals, (iii) the use of signals in pitching competition such as shark tanks and (iv) use of signals for startups exiting through initial public offerings (IPO's).

The existing research on signaling for the initial funding rounds has stressed the importance of forming associations with reliable third parties to build credibility (Plummer et al., 2016). Plummer et al. (2016) stress that new ventures can reduce investors' uncertainty by building positive attributes such as a strong board that includes industry or academic experts, showing market presence, and a management team. Venture capitalists often view these attributes positively as a validation of the venture's strength.

A perspective from personal experience on management teams is as follows. It is best if the teams are either unrelated or a team that has primarily worked or studied together. Close blood relatives often create the opposite, a negative association. In interaction with venture partners, many will not invest if the founders are either married to each other or are dating. On the other hand, academic associations build credibility, especially for high-technology startups.

Continuing the discussion on the importance of a third-party affiliation, daily et al. (2005) highlighted that the association is significant at the time of a fundraiser. Daily et al. (2005) simulated the need for credibility through an example of a startup seeking investors through an Initial Public Offering (IPO). At the same time, the information a listed company provides is standardized and regulated, hence considered credible. A startup's information is often considered exaggerated, incomplete, or even false.

A related use case to the one mentioned by Plummer et al. (2016) is the study from Islam et al. (2018). Recently, many researchers have focused on the fundraising challenges early-stage entrepreneurs face, with signals being considered as one of the significant factors. The challenge, though, is that even if we accept that signals help, early-stage startups usually do not have third-party affiliations and cannot generate significant signals. The information asymmetry is higher in the earlier stages (Plummer et al., 2016).

Plummer et al. (2016) suggested third-party affiliations through board members or employees or association with a venture development association (VDO) such as an accelerator or an incubator. Clouse and Austrian (2013) found a close association between early-stage funding and VDO affiliation. Some of the known VDOs are Y Combinator, Techstars, and Jumpstart. Roche et al. (2020) raised a similar argument concerning the academic qualifications of the founders. Roche et al. (2020) analyzed the academic qualifications of academic vs. nonacademic-backed startups. They found that while the exit valuation for both academic-backed and nonacademic-backed startups was similar, more academic-backed startups were able to raise funding.

Islam et al. (2018) further developed Plummer et al.'s (2016) argument by studying the link between government grants and subsequent venture capital funding. In a study of sustainability startups, Islam et al. (2018) found that startups associated with prestigious grants have a 12% better chance of raising initial venture capital financing. Secondly, Islam et al. (2018) also found that the signaling need was more significant for startups with fewer patents. Grants help by signaling technology and market potential that helps a startup differentiate from other startups in front of investors. Fisher et al. (2016) found that venture capitalists were willing to accept grants from reputed agencies to signal that the entrepreneur can cross the threshold from a conceptual idea to a commercial organization.

An essential contribution of Islam et al. (2018) is the startup lifecycle view and signals as a method to gain credibility in the most critical stage of the startup, when it must transition from idea conceptualization to an initial market acceptance or what is termed a product-market fit by the practitioners, in the startup world. This transition is important. Survival of startup is contingent on timely transitions between stages. The longer startups have their legitimacy questioned, the more likely they will encounter obstacles in obtaining the requisite external resources (Kraatz & Block, 2008). Funding is an important external resource that is the focus of this thesis. On funding, to highlight the importance of signals, we discuss a scenario of how signals can help a new firm get funding in a funding competition such as Shark Tank.

Shark Tank is one of the most famous reality TV shows that has been telecast on ABC (American Broadcasting Company) since 2009. In a shark tank, entrepreneurs can pitch their ideas to venture capitalists. Every season, only around 100 entrepreneurs qualify for the show, each allocated eleven minutes for a business pitch to a panel of investors. Any investor may find the business pitch lucrative and offer to continue the funding discussion. More often than not, no investor gets interested more often, and the entrepreneur may not get any funding interest.

In its design, Shark Tank is an event where entrepreneurs have a limited time to signal attractiveness as a potential business opportunity. Not surprisingly, research has established not the importance of signaling for Shark Tank fundraising but has also found patterns of signals that have led to maximum fundraising. The work of Lavanchy et al. (2022) is interesting in this context as it helps explain the case for signaling.

Modern finance theory is based on financial contracting, with the theory of adverse selection as one of its main principles. Oliver Hart and Bengt Holmström won the 2016 economic Nobel Prize on the theory of financial contracting (Nobel Prize, 2016). The basic premise in the theory of financial contracting specific to venture capital investments is that the entrepreneur will have more information about the startup as compared to the venture capital, and venture capital would assume this and try to build covenants that protect their investment interest. The same has been identified in the work of Lavanchy et al. (2022) with, them based their finding on signaling theory.

Lavanchy et al. (2022) found that entrepreneurs offering a lesser stake percentage were likelier to receive an investment interest during the Shark Tank pitching. By offering a lesser stake for a similar valuation, an entrepreneur signals their belief that the enterprise is expected to make significant progress and be profitable. Shark Tank is a live example and validation of the role that signals in the funding process. The examples, though, are of an early-stage startup that is seeking its first few rounds of funding. The same may apply to some of the use cases explored in this thesis but not to all of them.

Three use cases considered in this thesis could be impacted by signals.

1. Angel investors stage – These are startups seeking their initial funding with a basic conceptual idea and little or no operational data. The investors have very limited data points to validate the startup's business potential and will look for cues through signals. Patents and trademarks, which we will cover later, would be the most important cues, but in their absence, there will be other signals, which could be the initial traction or any other coverage, such as board members. Conti et al. (2011) found that family and friends funding is the main signal that are valued by the business angels.

2. Funded by venture capital and seeking further funding– The startups have been funded and are seeking an additional funding round. While their business model has been validated, historically, only 30% of the startups receive further funding, especially in the early stages. In this context, signals such as press news could

be an essential indicator of traction or help close the information asymmetry gap (Courtney et al., 2016).

3. Predicting survivability of an ESG startup – ESG is a new business area where the business model has not been proven. Like the case of a funded startup seeking further funding, we would expect press releases and signals to help close the information asymmetry (Courtney et al., 2016).

In this thesis, we use two different indicators of signals. Initial traction and board members would be an estimate of signals in the angel investor phase. In contrast, we estimate signal strength based on the quantum of press releases for the funded startups seeking further funding and ESG startups seeking survivability.

The impact on venture capital efficiency must be tested. This would be tested for venture capital follow-on funding and survivability. For angel investors, the thesis will be focused on helping startups with cues for funding. Thus, the hypotheses are.

H_7 – For angel investors, signals provide positive validation and help with the funding.

H_{8a} – For venture capital-funded startups seeking further funding, the number of press articles helps provide positive validation for funding.

H_{8b} – Where the business model is not proven, the number of press articles provides positive validation of the strength of the business case and the survivability of the startup.

The summary of findings and discussions are in Table 20 below.

Table 20- Summary of signals findings.

Discussion area	**Main discussion**
Previous research	• Research has indicated that cues are important for startups raising funds. This has been evidenced by study of grants, cues, press articles, and events such as shark tank.
Gap being tested	Three gaps • The theory mainly supports signals as cues for funding. The thesis explores signals as tools for improving venture capital returns. • Do signals help with the first check. • Are signals signs of a startup's survivability.
Segment being tested	• First funding • Follow on funding. • Survivability
Expected conclusion if analysis failed to reject the hypothesis	• Signals become important for venture capital as signs for driving funding efficiency. • Signals are important cues for first funding. • Signals can help indicate survivability.

Patents

Patents are rights granted to a person or an organization that protects his or her right to commercialize the technology associated with the innovation that has been patented. Officially, the World Trade Organization has one of the best definitions of a patent. WTO (2019) defines patents as the title given to the Intellectual property right that is granted to protect new inventions. A patent granted by the authorities in a specified jurisdiction gives its owner an exclusive right to prevent others from exploiting the patented invention in that jurisdiction for a limited period without authorization.

Many of the startups, especially the ones that originate from a university, are based on the unique technology developed by the founders. In the context of this thesis, this is also one of the leading indicators of innovation. Patents are important for the following reasons.

1. Previous research has indicated that patents are correlated with revenue growth (Yun et. al., 2021; Neuhäusler et. al., 2011). Revenue correlation is critical for venture capital returns and exit.
2. Patents as signals of innovation, are key to this thesis. The assumption is that innovation drives productivity and economic growth and should be relevant for a venture capitalist. Patent should lead to greater funding efficiency. This assumption would be tested in this thesis.
3. Patents can also play a signaling role ensuring funding. As indicated in figure 9, lack of funding is a major reason for startup failure. Startup failure would imply lost investments for the venture capitalist investors.

Patents as signals are important. Startups have limited historical and operational data, increasing the fund-raising challenge. To raise funds, startups need to differentiate from other startups and be among the few that the venture capitalist decides to fund. Without operational and historical data, the startups can rely on cues or signals to build their case. Patents are one such cue and are extremely important in the context of this thesis. It is also important to note that this cue or signaling is due to the protection provided by the patent and the expectation that the technology will be commercialized through the startup. There are nuances in patents across the regions and it is important to note that the patenting process is not universally similar. Patents assigned by some regions may be considered more valuable by venture capitalists.

Four things are important to note. First, the right applies to a particular jurisdiction. By this definition, a US or European patent would be more valuable than an Asian or African patent, where the coverage may be restricted. Second, there needs to be a definition of what makes an innovation consistent with the intellectual property offices in the nations. Some nations stress that innovation refers to a new product, whereas others also incorporate new processes as an innovation. As a result, some nations have product patents, whereas others have process patents. Third, patent protection is applicable for a limited time, usually twenty years. Finally, some experts believe that patents must be litigated to verify whether they can be enforced.

In the context of funding, patents have been viewed patents from a signaling theory perspective with its importance as a cue. In this study, it is (i) important to verify whether signaling theory holds for patents, (ii) whether patents are a driver of funding in both the early and the late stages, (iii) do patents help with survivability and exit, and (iv) with locational differences, is it fair to assume that patents would be equally valued across different geographies, i.e., in the US, Europe, or Asia. Finally in the context of this thesis, whether patents help drive greater efficiency and returns to a venture capital? This would need to be tested through impact of patents on a startup exit through an initial public offering or through mergers and acquisitions.

In the context of signaling, one of the questions that has bothered researchers is why firms invest in patents, especially when, on average, the appropriability value is low (Conti et al., 2013). Their view is that patents are used as signals to attract "new investors." The operative phrase is "new investors," and Conti et al. (2013) opined that it did not have the same effect on "old investors" or investors who had previously invested in the startup. In this context, it can also be assumed that patents as signals, would have the highest value if the patent has been granted during earlier rounds of funding. The affect may not be the same during the later funding rounds. In the initial rounds, patents can be strong signals of commercialization potential whereas in the later stages, patent would imply more of commercial protection (Conti et al., 2013). The question was whether patents were purely technological advancements being commercialized as innovations or whether they planned a signaling role to venture capitalists and investors. Conti et al. (2013) concluded that patents, in addition to technology innovation, were being deployed as signals.

The fact that smaller, capital-constrained firms have a greater propensity to invest in patents as compared to capital-positive, larger firms drove Conti et al. (2013) to this conclusion. Even the Berkeley Patent Survey found that one of the most important reasons for startups to patent was to secure financing, as identified in the works of Graham and Sichelman (2008) and Graham et al. (2009), quoted in Conti et al.

Greenberg (2013) has a similar view, stressing that the market for entrepreneur finance is inefficient and needs signals for entrepreneurs to attract investors. The need is especially crucial for new ventures that lack the quality of tangible assets and hence use innovation as signals.

So why would patents be that signal? The answer lies in the financial contracting theory, where concepts of moral hazard and adverse selection would play a significant role in catapulting patents as a possible solution to signaling innovation. In this context, patents play a role like grants, which we discussed in the earlier parts of this section.

The two main reasons that patents can be effective as signaling cues is (i) in the vacuum of complete knowledge, venture capitalist run a risk of identifying the right investment opportunities, and (ii) corporate history is unfortunately full of cases where venture capitalist has expropriated an entrepreneur's IP. In the context of the second point, Toshiba illegally transferred a startup's technology within its portfolio to a rival venture, and AMD and Fujistsu were sued for similar transgressions (Greenberg, 2013). Hsu and Ziedonis (2008) have also added that patents could be a potent signal in this context as they should protec' against the misappropriation of ideas disclosed during negotiations. Hsu and Ziedonis (2008) evaluated 813 US startups where they found a direct link between patents and a startup valuation, with patents increasing the value by 28%.

While patents are positive signals for valuation, their link with funding needs to be evaluated and will be tested in this thesis. Also, it needs to be ascertained whether patents are the right signals for a venture capitalist to maximize its return by investing in a startup that has been granted a patent. This thesis has three parts: (i) early stage / first funding, (ii) existing funded AI startups seeking further funding, and (iii) survivability of the startup and its final exit. The role of patents will need to be discussed for each of these stages.

There are three dimensions to reviewing patents across these stages: (i) appropriability, (ii) signaling effect, and (iii) usefulness of the patent. Again, there are two views on the applicability of patents by stage of startup development and funding. Some researchers believe the patent would be more valuable during the initial stages of startup development, whereas others believe it would be better during the late stages (Conti et al., 2013). Let us discuss the specific value propositions for each investor and stage, as this would be important for the construction of this thesis.

First, not all patents may be necessary. Hall (2006) interviewed 351 managers who received seed funding and found that 30% had valuable patents, and 10% had patents that Hall (2006) classified as not that valuable. There was a correlation between funding and startups with useful patents. This seems counter to the view of Hsu and Ziedonis (2006), who suggested that startups invest in patents in the early stage, as that is when they can effectively act as a signal to attract funding.

One of the primary challenges concerning early-stage startups and patents is the limitation to appropriate the benefits from a patent, which is not an issue in the later stages (Mann, 2005). Also, the challenges are higher for industries such as AI and software, where appropriability depends on many factors, including the complexity of a software product. Software products have multiple components and need a series of patents to ensure that the product or process cannot be duplicated (Mann, 2005). Overall, the following results have been documented by previous academicians.

1. Mann and Sager (2005). – Firms with patents are four times more likely to have an IPO than firms without a patent.
2. Helmers and Rogers (2011). – Patentees have a higher growth rate than non-patentees. The growth rate witnessed by patentees is between 8% and 27%.
3. Hsu and Ziedonis (2013). – An additional patent application increases the valuation by 40%.
4. Balasubramanian and Sivadasan (2011). – A patent increases the size of the firm by 15%.
5. Farre-Mensa et al. (2017). – A startup with a first-time patent approval leads to a 55% higher employment rate and 80% higher sales growth after five years.

These strong results are expected to influence startup funding, survivability, exit, and growth impacting venture capitals returns and funding efficiency. Yet, we see that the patent process differs globally and significantly by region. While much has been written about the different patent standards across different regions, the best comparison is between the processes followed at the US patent trade office and the European Patent Office. Both have significant sizes, cater to a similar market size, and tend to be very different. Graham et al. (2002) compared the two processes in their working paper submitted to the National Bureau of Economic Research (NBER).

Graham et al. (2002) considered the patents for similar inventions in both the European Patent Office (EPO) and The US Patents and Trademark Office (USPTO). On average, a valuable patent was challenged thirty times more in EPO than in USPTO. Each challenge is important, as 41% of the challenges are successful. Based on this, there are regional differences, and hence, venture capital may accord different importance to these patents.

Based on this discussion, the hypothesis to be tested will be as follows:

H_{9a} – For early-stage startups, patents will influence the fundability of a startup.

H_{9b} – Where the startups have been funded once, patents would be important factors influencing funding efficiency.

H_{9c} – Patents would impact the exit and hence are valuable for venture capital.

H_{9d} – There are regional differences in the importance and impact of patents as funding factors.

The summary of findings and discussions are in Table 21 below.

Table 21- Summary of patents findings.

Discussion area	Main discussion
Previous research	There is previous research around. • Patents as cues that enable a startup to receive venture capital funding. • Patents being more valuable in the initial stages of funding as compared to later stages. • Patents appropriability varies. • Patents usually lead to revenue and economic growth.
Gap being tested	Four gaps • Correlation between patents and venture capital returns (not startup seeking funding). • Impact of patents on survivability and exit of the startup. • Are patents as important across regions? • Sector specific analysis of a high technology area such as artificial intelligence and impact of patents on funding and returns.
Segment being tested	• First funding • Follow on funding. • Survivability
Expected conclusion if analysis failed to reject the hypothesis	• Correlation between patents and exit. • Regional differences. Where patents help both the startup and the venture capitalist. • Correlation between patents and returns for high technology artificial intelligence startups.

Trademarks

International Trademark Association (2023) defines a trademark as any word, name, symbol, or device (or any combination thereof) that identifies and distinguishes the source of the goods of one party from those of others. Trademarks are essential for a startup and an important consideration for investors. For investors they indicate commercialization of intellectual property. Commercialization is an important aspect of an exit (Chammassian & Sabatier,2020; Furnari, 2015) and denotes whether a startup can be successful.

Both patents and trademarks protect the IP of the startups, though they look at different aspects of trade secrets (Vries et al., 2021; Block et al., 2015). Patents refer to the technological aspects of the startup's business model, whereas trademarks refer to the marketing aspects of the startup's business model (Vries et al., 2021).

While Block et al. (2015) have established that trademarks can attract venture capital funding, recent scholarship has focused on the confluence of patents and trademarks. Scholars have argued that the startup's benefits from an innovation depend on its ability to commercialize the technology (Chammassian & Sabatier,2020; Furnari, 2015; Thoma, 2021).

The multifarious role of trademarks presents an interesting challenge for this thesis. On the one hand, they can be signals for valuation and funding. Secondly, they need to integrate with patents, with the combination of patent and trademark being significantly more valuable to an investor than each one of these independently. Finally, as per research from Fisch et al. (2022) and Zhou et al. (2016), trademarks increase the survival probability and lead to higher valuation at IPO. Each of these challenges needs to be considered in the context of the tests conducted in this thesis.

1. Early-stage startups seeking their first funding – One of the models built in this thesis is around pre-seed startups seeking funding from an accelerator. The accelerator in US-based accelerator, and the first funding offered was around $100k. These were largely pre-revenue startups, and there was little to differentiate in the business models. In the context of this category, signals are important for investors to fund a startup. Also, realistically, in this category, the

startup may have a patent but would be without a trademark. On the other hand, if a startup has a trademark, it will be more likely to receive funding, as a trademark would imply commercial readiness and investor returns. In the case of first funding, signed clients may be an indicator of commercial readiness hence the hypothesis needs to be broader than just a trademark to:

H_{10a} – *If a pre-seed startup has registered a trademark or has live clients, it is more likely to receive funding.*

2. Artificial intelligence startups that are seeking further rounds of funding – These are startups that have received their initial rounds of funding and are seeking further funding. Our study in this context is on readiness for further rounds of funding. Whether the startup should be funded, and if funded, would it be able to show revenue growth traction? As discussed in this section, the combination of patents and trademarks would help denote a proprietary product supported by commercialization initiatives. At the same time, given that artificial intelligence is like software and patenting limitations in software have been discussed, we would expect that trademarks, by themselves, should also constitute a significant push toward funding. Venture capitalists would view these as startups that have transitioned from pre revenue to revenue stage and have independent marketing presence that will help them grow the business. Business growth as indicated earlier would translate into venture capital returns. Hence the hypotheses

H_{10b}– *The combination of patents and trademarks should influence a venture capital funding decision.*

H_{10c} – Venture capitalists consider trademarks to be a significant factor influencing the funding level.

3. The final test of investment is a successful exit, which depends on the startup's survivability and its IPO or acquisition. In this thesis, we are testing the factors that help predict a sustainability startup's survivability. Trademarks should positively impact survivability as it would indicate commercial readiness. Hence the hypotheses

H_{10d} – The presence of trademarks would increase the chances of a startup's survivability.

The summary of findings and discussions are in Table 22 below.

Table 22- Summary of trademarks findings.

Discussion area	Main discussion
Previous research	There is previous research around. • Trademarks, in the context of startups, are considered as indicators of commercial readiness. • As commercial readiness indicator, they help to drive funding to a startup.

Gap being tested	• Venture capitalists' returns are dependent on exit, and that needs commercialization of technology. Is there evidence to prove that trademarks can help commercialization; protect investment by.
	  o Follow-on funding. Generating value if correlation is positive.
	  o Survivability of a startup.
	• In the current context, is there a correlation between a startups first funding and trademark / commercial activity.
	• Is the cross product of trademarks and patents significantly correlated with funding efficiency.

Segment being tested	• First funding • Follow on funding. • Survivability
Expected conclusion if analysis failed to reject the hypothesis	• Correlation between trademarks and return. • Importance of trademarks or commercial live as a factor for first funding by accelerators or angel investors. • Correlation between trademark and exit.

What are the differences between the two main investor types – venture capital and angel investors – that are important for a startup?

This section of the thesis is focused on entrepreneurs rather than venture capitalists. As noted in the earlier sections of the thesis, they need specific advice on what could be driving funding in today's sentiment. Good quality startups with first funding also helps in creating supply for venture capitalist. While we have discussed multiple funding factors, they will differ by investor type.

As a class, investors may have different risk appetite and return needs. Usually, there are two main types of investors. One is people who invest their funds, i.e., accredited investors who could be angel investors and investors who manage funds raised from institutional investors, mainly pension funds. Venture capital falls within the latter. The difference between these investors can be summarized in table 23 below.

Figure 23 – Comparison of different forms of investors

Comparison heading	Venture capital	Angel investors
Sources of funds	Large institutional investors, usually pension funds.	Own funding, usually accredited investors
Basic capital characteristic	Expertise and mentorship with a proven network	Passionate supporter
Investment responsibility – who bears the loss	Limited. Largely of the institutions	Personal funds
Investment experience and capacity	Large experience and capacity	Limited capacity and experience
Due diligence	Extensive due diligence	Limited due diligence
Operational engagement	Few hours a month	Few hours a week
Investment stage	Seed to later	Very early stage
Exit strategy	Very important	Not that important
Investment holding period	3-5 years	3-8 years

Source: Avdeitchikova et al. (2008), Original research (2023)

These two investors are representative of individual and mainly institutional investors. The list of investor types is incomplete, and two other investors, family offices and private equity players, are important. SPAC (special purpose acquisition companies) also play a role in the exit.

While selecting the factors that could drive funding, it was mentioned that these factors could be significant for a venture capitalist in most cases and an accelerator in some cases, the focus of this thesis. From a venture life cycle perspective, angel investors, as an investor class, cannot be ignored.

Some of the main roles played by angel investors are listed below. As defined earlier, angel investors are wealthy individuals who invest their personal funds into early-stage firms. In addition to funding, they tend to contribute industry and managerial expertise to the entrepreneur (You, 2000). Why is this segment important in the context of this study?

1. Venture capitalists usually invest from seed round onwards. The seed round is when the startup seeks to build early momentum. Significant investment is required before the initial pilot cases' seed round for proof of concept. Usually, funding for a startup is with entrepreneur savings first, followed by friends and family, then angel investors, and then venture capital. The details are in Figure 13, which was mentioned earlier in this thesis. We will also be testing their funding criteria in this thesis. One of the use cases is to check whether data algorithms are conducive at the earliest round – pre-seed round. Usually, only accelerators and angel investors invest in this round.
2. Angel investors complement the role played by venture capitalists in innovation introduction and economic development by providing the first external source of funding usually used for proof of concept.
3. Angel investors normally invest as they are passionate about the industry and can help the startup find initial traction. They play a critical role in the survivability of a startup.
4. It is important to also ensure angel investor profitability that comes both because of first funding and follow-on venture capital funding. Their numbers have been stagnant for some time. As per CMC Data (2021), in the USA alone, there are 13.65MM accredited investors (10.6% of the population), but only 300k are active in the market (2% of the accredited investors). Accredited investors, as per SEC, are the investors that are allowed to invest in private assets (angel investors).

Based on these criteria, it is not difficult to understand that angel investors would have different funding criteria. Since we cover the entire life cycle for venture capital from pre-seed to exit, we should understand the factors that influence an angel investor’s funding. The top factors analyzed from the search can be viewed in Figure 24 below.

Figure 24 – Top factors influencing angel investors’ funding.

Pillar of Decision-Making	As per the top 3 Research (>150 samples)
Product	Is it of personal interest Is it protectable Is it innovative
Market	What is the Market Size What is the growth potential? Customer engagement Market dynamics/competition
Entrepreneur	Industry Experience Track record Passion / Commitment Integrity Technology Use & Knowledge
Financials	Profitable/ Realistic Plan Capitalization/ Cash Flow estimates Size of investment ROI / Valuation
Investment	Team characteristics Business Fit (Market / Structure) Location Referral/ Co-investment

Source: Maxwell et al. (2011)

The stress during first funding is based on data and qualitative factors. Many of the practitioners often call this as a mix of art and science. It is still important to probe whether the pre-seed stage can be more data driven. This would be important. As per Forbes and CNBC, accredited investors are hesitant to invest in private equity due to the lack of opacity, liquidity, and S&P generating more than 10% with liquidity. Data-driven models can help bring in transparency and predictability. By enabling more first funding to be funded, angel investors could be creating a pipeline of good quality startups for venture capital to fund.

Every venture capital has a minimum ticket size below which they do not invest in the startup (Schwarzkopf et al., 2010). Those investments could be more economically viable for the venture capital fund. Usually, the ticket size corresponds to growth stage funding and not at the proof-of-concept stage. Table 25 explains the link between angel investor funding and venture capital funding along with the stages of product development to highlight the importance of the first funding. The founder needs those small cheques, and that is where angel investors and accelerators fit in the ecosystem growth.

Figure 25 – Importance of angel investor funding.

Funding stage	Funding Sources	Product Development Stage
Pre Seed	Boot strapping, angel investors, grants, crowd funding, accelerators	Mock-up, demonstration, prototype, MVP
Seed	Angel investors, some Venture capital funds, accelerators, crowd funding, seed funds	MVP, Beta, Product Launch
Pre-Series A	Business angels, seed funds, venture capitals, crowdfunding	Product on the market, product market fit
Series A	Mainly VC	Ready product, proven product market fit
Series B	VC funds, Corporates (M&A, LBO, Corporate VC), technology oriented private equity firms	Mature product
Series C	Private equity, venture capital, corporates, Banks	Mature product, new products, acquisitions
Exit to IPO	Bank funds, public through IPO	Mature product with significant revenue potential

Source: Burak (2023)

Only angel investor or accelerator funding is available till the prototype stage, and that is usually not enough for the full product and market development. Y Combinator, one of the topmost accelerators, writes a maximum of US$500,000, while other accelerators are in the range of US$200,000. Angel Investors typically write much smaller cheques of US$ 25,000- US$50,000 (Kakar, 2023, market experience); these angel investors and accelerators help fund the startup at an early stage when the founder needs funds to prove his or her case.

Venture capitalist then helps drive commercially viable products leading to innovation. However, the link between angel investors and venture capitalist is important. As stated earlier, venture capital as a funding model, originated due to the need to provide risk equity where the founders could not guarantee a collateral for a bank loan. The same applies to angel investors. They provide money to a startup founder to validate the business case. Also, they have the same challenges as a venture capitalist of a small percentage of ventures succeeding. That is one of the reasons that the numbers of angel investors are a small percentage of total available accredited investors. Their challenges also need to be addressed.

Next, we look at practical and historical research on why data frameworks may be able to address the challenge better.

Previous research on the use of data analytics for startup due diligence

Like mentioned earlier, there have been previous research notes that have focused on the use of data models for startup valuations and funding. Most of these have focused on factors that will help startup by either helping them get funded or by helping them increase their valuation. This thesis, focusing on increasing venture capital return, is one of the few one’s that is addressing this problem. There are gaps that have been identified in the previous segment that need to be addressed. Efforts have also been made to make this thesis relevant for both the academic and the practical world.

This thesis looks at the subject from both an academic and a practical perspective. One of the questions that has often been raised during interaction with professionals relates to the fact that while artificial intelligence and machine learning create a possibility for significant transformation of financial services, their use in credit decisions has been limited due to what is known as a “black box” impact.

“Black box” in this context is the lack of explainability of algorithms such as neural networks. Lack of explainability, especially in credit and risk, may not be acceptable to the regulators. For example, the recent European Union artificial intelligence policy states credit as high-risk artificial intelligence (Press release, EU, 2023)

High risk artificial intelligence has the following obligations that must be adhered to

1. Fundamental rights impact assessment
2. **Data governance requirements.**
    a. **Bias mitigation**
    b. Representative training data.
3. **Transparency**
4. Risk management and quality management systems
5. **Human oversight including explainability.**

This thesis proposes an algorithmic approach for a startup’s due diligence, an area that falls within the credit and risk functions. Therefore, this thesis avoids ensemble methods and focuses on explainable algorithms.

Before we proceed to the data models, feature importance, and analysis in this thesis, it is important to understand some of the risks associated with the use of machine learning in financial services. The acceptability of data models needs to be established withing the purview of regulatorily permissible techniques and current established use cases where knowledge can be extended to provide justification for the use cases discussed in this thesis.

Risks associated with machine learning in financial services.

Embedded bias, black box, cybersecurity, data privacy, robustness, and impact on financial stability are some of the risks identified in an IMF study (Boukherouaa et al., 2021). For this thesis, it is important to understand what these risks are, the impact they can have on this thesis, and how they are being addressed in this study. To confirm with the recent guidelines, the proposed methodology would need to take these into account.

The details are in Table 26.

Table 26 – Risks associated with the use of an algorithmic approach and how it is being addressed.

Identified risk	Definition	Impact on an algorithmic approach towards startup funding Readiness Due diligence	Actions used to mitigate the risk – during thesis analysis / while going live
Data bias	Customer categorization challenges that will lead to computer systems that will systematically discriminate against some individuals	• It is challenging to obtain counterfactual data as data is within venture capital databases. • Historical funding has been heuristic-based – inbuilt bias to some extent.	• Selective use cases with lower risk of bias– funded startups ready for – the next round of funding and survivability • Relied largely on public data and categorization to remove selection bias.
Black box	Explainability is a complex topic and includes: (1) they are complicated and cannot be easily interpreted, (2) their input signals might not be known, and (3) they are an ensemble of models rather than a single independent mode.	• Ensemble models and neural networks give the best results but lack explainability. • The thesis is focused on identifying the right factors. Lack of explainability will cause the findings to fail.	• The data models built in this thesis are largely based on regression modeling and do not include ensemble or deep network models.
Cybersecurity	AI/ML are susceptible to novel threats that involve manipulating data at some point during the training cycle.	• No such threat in this study	• No action taken
Data privacy	Data privacy risks are emerging from AI's ability to unmask data based on behavioral patterns. It also includes the use of data without consent.	• An algorithmic model has been constructed, and that needs data. Data has to be ethically sourced. .	• Only public/masked data was used for the entire exercise.
Robustness	The algorithm must establish trust within the financial services sector.	• The exercise could be a one-time algorithm that may not be tested over a period of time.	Two steps were taken. • Only factors that were proven academically were selected in the model. • Limited longitudinal testing was conducted.
Impact on financial stability	More of the transformational impact on financial services employment, etc.	None	None

Source: Boukherouaa et. al., (2021), own actions

From a practical standpoint, the thesis needs to establish that similar use cases have been accepted in practice. In this context, a good case is a study by the OECD (2021) that lists the practical use cases for AI deployment in finance. The details are in Figure 27.

Figure 27 – Acceptable use cases for artificial intelligence and machine learning in finance

Asset Management • Identify signals capture underlying relationships in big data. • Optimize operational workflow risk management. • Potentially alpha generating.	**Credit Intermediation** • Reduce underwriting costs inefficiencies. • Credit extension to thin files/ unscored clients. • Financial inclusion and SME financing gaps
Algorithmic trading • Enhance risk management/liquidity management. • Facilitate the flow of large orders and optimize order flow.	**Blockchain-based finance.** • Augment capability for automated finance (smart contracts). • Risk management. • Support DeFI application deployment.

Source: OECD (2021)

Risk management is common in all OECD recommendations, and this fits well with the objective of this thesis. Also, signaling is consistent with the discussions till now. The OECD (2021) report includes a discussion on asset management, venture capital is a form of asset management. The discussion in OECD (2021) is limited to portfolio rebalancing and not to new investments. That is where the thesis highlights new practical applications by extending the knowledge to new investments. The thesis also mentions two practical use cases implemented for investors that further validates the practical application.

. On academic validation, while the aspect of startup due diligence leveraging machine learning has not been extensively covered, limited academic research publications indicate the possibility of developing it within this thesis. The existing research covers parts of the process and only includes part of the lifecycle view of pre-seed, follow-on funding, survivability, and exit. Also, it does not cover gaps mentioned earlier in the thesis.

Historical research on data models for startup funding

Many eminent scholars have researched the deployment of machine learning and data-centered approaches to estimate the startup's risk and valuation. It would be naïve to assume that this is the first attempt as we are in a data-focused society with artificial intelligence widely applied, and data are rapidly becoming the crux of most predictions and decision-making. While there are examples of application of a data-based approach, there are still gaps in existing research. Some have been stated earlier. The key ones are summarized below.

1. The focus is on helping an entrepreneur raise funding and not on helping a venture capital funding process become more efficient. These two theses are significantly different.
2. The focus is on valuation and not funding. As discussed earlier, valuation is the total price of the startup whereas funding is what is being invested, hence the more important value from this thesis perspective.
3. The link of venture capital funding with innovation and economic development is still a gap, and hence, the complete cycle from pre-seed to exit is not covered. Patents were also one of the factors, but not the most significant. Most of the research has been at a point in time and has excluded the longitudinal analysis.
4. Regional differences have been ignored, and that is not practical. Funding behavior and thesis vary for the US, Europe, and Asia.

But before proceeding to research methodology, data analysis, findings, and discussions in this thesis, let us consider the main papers that have explored a machine learning and data analytics methodology for venture capital funding. A summary of the main research is in Table 28.

Table 28 – A summary of the main research on use of a data modeling for startup financing

Reference	Dataset	Method
Miloud et al. (2012)	Thomson Financial Security Data	Regression
Prohorovs et al. (2019)	Primary data obtained by a survey	Factor analysis and regression data
Krishna et al. (2016)	Crunchbase	Machine learning
Weking et al. (2019)	Crunchbase	Contingency analysis
Dellerman et al. (2018)	Crunchbase, Mattermark, Dealroom	Machine Learning
Sharchilev et al. (2018)	Crunchbase, LinkedIn, Mentions from other platforms	Web-based startup success prediction (own model that is a mix of techniques)
Tomy and Pardede ((2018)	2013). Victoria ICT statistics survey	Machine learning
Arroyo et. al. (2019)	Crunchbase	Machine learning
Kaiser and Kuhn (2020)	Danish Business Authority	Logistic regression
Ross et al. (2021)	Crunchbase, USPTO	Machine learning
Zbikowski ˙ and Antosiuk (2021)	Crunchbase	Machine learning

Source: Kim et al. (2023)

Next, we validate whether the funding factors identified earlier in the thesis have been covered in these studies as important factors. Due to different studies leveraging different data sets, a common set of factors is difficult to consider, and the thesis has to identify common factors that have leveraged similar dataset. This thesis has leveraged CrunchBase datasets, so the focus is only on using research papers that have used CrunchBase as the dataset. Crunchbase is also used by majority of the datasets. The details are in Table 29 below.

Table 29 – Some of the factors used in previous studies.

Theme	Factor used	Description
Company Details	Company Type	Whether this company is for-profit or for non-profit
	Company Popularity	Number of customers that have visited the site in the last six months
	Company attractiveness	Average number of pages viewed in the last month
	Company age	Age of the company
	Employees	Number of employees
	HQ location	Whether the HQ is in Silicon Valley, New York, or London
	Exposures	Number of press articles
Funding	Funding recency	Whether this company has received funding in the recent 3 years
	Funding frequency	How often has the company received funding
	Funding monetary	How much funding amount has this company received
Investors	Top investor type	Whether the investor is an accelerator
	Involvement of top investors	Whether the top 10 investors are involved in the company
	Number of lead investors	The total number of lead investors
	Total number of investors	The total number of investors
Technology	Amount of technology available	Amount of technology available to the company
	Number of applications	Total number of applications built
	Total download of applications	Total number of applications downloaded
	Number of patents	Number of patents
	Number of trademarks	Number of trademarks
	IT Spend	Total amount of IT dollars spent

Source: Kim et al. (2023)

These factors largely align with the hypothesis mentioned earlier and would be good to be tested. A point to mention is that the previous studies have found that only a few of these would apply in a situation, and that is what we intend to explore with (i) a view on the startup lifecycle from pre-seed to exit, (ii) from an industry-specific approach, and (iii) from a region comparison of factors.

Table 28 also indicates that among the possible approaches, most academicians have preferred regression, and CrunchBase datasets have the highest acceptance.

Regression is preferred as it helps avoid the “Blackbox” approach with a greater level of transparency in feature significance and weightage. As mentioned earlier in the thesis, the venture capital SEC regulatory requirements and the new EU artificial intelligence requirement introduces a higher need for explainability and transparency. Also, most central banks regulations require explainability. In the Asian context, Buckley et al. (2021) highlighted explainable AI as a requirement of most of the larger regulators. They cited explainability as a requirement from World Economic Forum overall, and requirement from Monetary Authority of Singapore (MAS) and Hong Kong Monetary Authority (HKMA) requiring explainability.

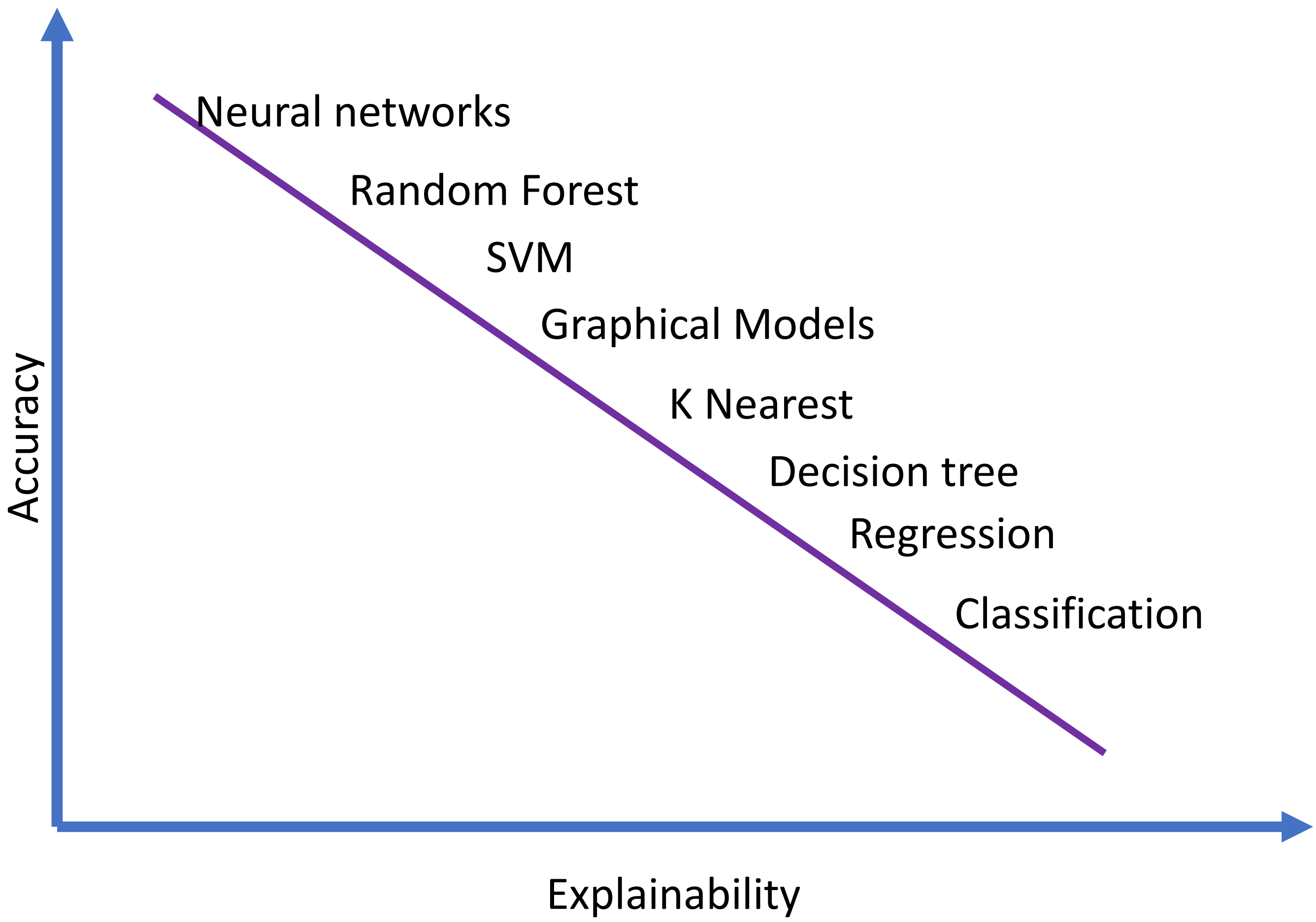
EU has been taking the lead in demanding explainability through its new framework that is also expected to address the privacy laws and explainability related to Generative AI. Even the previous ones required transparency. European Commission’s proposal for a regulation laying down harmonized rules on AI (April 2021) stated that lack of explainability may lead to discrimination and power imbalance as the right to a fair trial and effective remedy is a fundamental right of the consumer. In financial services, consumers have a right to know why their credit application or proposal was declined. The central banks usually mandate this transparency to avoid and dissuade implicit bias.

Similarly, in the US Board of Governors for Federal Reserve (2021) speech, Governor Lael Brainard stressed that the absence of explainable AI will not be acceptable to the regulators as it may encourage implicit bias based on race or gender. Overall, the Federal Reserve has reiterated this stand in its latest statements. But then, how does this affect the venture capital industry?

While previously, the venture capital industry was largely a relationship between a Limited Partner (LP) and a General Partner (GP), the rules of the game are changing for the venture capital industry. Recently, the Securities and Exchange Commission (SEC, 2023) issued and adopted (August 2023) new private fund advisor rules that call for greater transparency and increased reporting. We had covered these regulations in the previous sections.

Before we proceed with the next steps of research methodology and thesis data analysis, it is important to understand that while regression fits the business and regulatory needs best, there may be more accurate methods to deploy. An interpretation of explainability vs accuracy is detailed in Figure 30.

Figure 30 – Accuracy v/s explainability tradeoff, Machine learning models



Source: Srivastava (2021)

Regression has relatively lower accuracy but high explainability among the data analytics and machine learning models. This creates a new challenge for this thesis.

1. For the thesis to have a practical application, the thesis must use a method that could be applied in practice. That would be regression, i.e., it is explainable, and all regulators expect data models used in financial institutions to be explainable.
2. It may not be the most accurate method, and the reader may always want it to be validated with different methods for the results to be accepted.

To overcome the accuracy challenge, the thesis relied largely on regression-based testing but supplemented it with longitudinal testing, i.e., testing the same data set over two different years and checking whether the first results were accurate. The check in the first year is a data-driven algorithm, whereas the following year's check was qualitative based on the events reported past the first-year results. For 81 artificial intelligence startups considered as a sample within this thesis, average fund raise was every 1.5 years. One year is a good midpoint check.

This step was required for the thesis to be aligned with the intent of ensuring venture capital's profitability and efficiency. There would be two measures for each scenario.

1. The factor significance as denoted by the model.
2. The year-on-year results.

With that in mind, the thesis now focuses on the research methodology.

Research Methodology

Before we proceed, a few areas need to be discussed. (i) How does the hypothesis help answer the research questions? (ii) What should be the target population to study? (iii) What are the preferred research methods? (iv) What is the collection strategy? Also, as discussed earlier in the study, startups have different phases of development, and venture capital funding is linked to each stage separately. Also, the final return for a venture capitalist is on exit.

In this context, we will define three phases of venture capital development that we will consider for this study.

P_1 – Pre seed or the first funding stage.

P_2 – Follow on funding.

P_3 – At exit

A simple table, Table 31, has been documented below to demonstrate this. The table includes hypothesis, the research question it is answering, the stage (P_1-P_3), and the deep dive startup segment (universal for pre-seed, artificial intelligence, or sustainability).

Table 31 – Mapping of hypothesis to the research questions.

Follow-on Funding test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_1	For similar industry segments, the number of employees will be a significant factor in the follow-on funding.	2 - Relative importance of other factors $1_{a,\ b}$ - Can machine learning models fit in selecting next stage of funding	The focus has been on qualification of employees but never on the fact that an ability to attract employees is a positive validation of the startup and should provide confidence to the venture capitalist that the startup can scale.	Artificial intelligence	The thesis stresses that venture capital helps innovation. Artificial intelligence is a technology innovation area
H_4	The number of software applications developed by a startup will be positive correlated with VC funding raised.	2 - Relative importance of other factors $1_{a,\ b}$ - Can machine learning models fit in selecting next stage of funding	In a standard industry segment such as artificial intelligence, it is not enough to invest in technology but to create differentiation. Differentiation will be tested as a part of the patents testing.	Artificial intelligence	The thesis stresses that venture capital helps innovation. Artificial intelligence is a technology innovation area
H_{8a}	For venture capital funded startups seeking further funding, the number of press articles help provide positive validation for funding.	2 - Relative importance of other factors $1_{a,\ b}$ - Can machine learning models fit in selecting next stage of funding	The theory mainly supports signals as cues for funding. The thesis explores signals as tools for improving venture capital returns.	Artificial intelligence	The thesis stresses that venture capital helps innovation. Artificial intelligence is a technology innovation area
H_{9b}	Where the startups have been funded once, patents would be important factors influencing funding efficiency	2 - Relative importance of other factors $1_{a,\ b}$ - Can machine learning models fit in selecting next stage of funding	Patents as signals for commercial opportunity	Artificial intelligence	The thesis stresses that venture capital helps innovation. Artificial intelligence is a technology innovation area

Follow-on Funding test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_{9d}	There are regional differences in the importance and impact of patents as funding factors.	3- The factors will vary by the region.	Correlation between patents and venture capital returns (not startup seeking funding).	Artificial intelligence	There are regional differences in issuance of patents. These factors may strengthen patents as signals in some regions, and in some regions, it may weaken
H_{10b}	The combination of patents and trademarks should influence a venture capitals funding decision.	2 - Relative importance of other factors $1_{a,\,b}$ - Can machine learning models fit in selecting next stage of funding	Is the combination of trademarks and patents significant for commercialization and hence returns to the venture capitalist	Artificial intelligence	To check whether and ability to commercialize technology plays an important role in convincing investors to fund
H_{10c}	Venture capitalists would consider trademark as a significant factor influencing the funding level.	2 - Relative importance of other factors $1_{a,\,b}$ - Can machine learning models fit in selecting next stage of funding	Does trademark provide greater comfort to a venture capital of possible returns	Artificial intelligence	The thesis stresses that venture capital helps innovation. Artificial intelligence is a technology innovation area. Trademarks helps in commercializing technology

Survivability / Exit test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_3	Greater market size will be a key feature for startups in business areas where the business model is under development.	1c - Survivability of the startup	Does market size help a venture capitalist estimate idiosyncratic risk for a new segment?	Sustainability	New, emerging, business models that could be difficult to convince market
H_5	In a new industry, previous founder professional experience may be significant to develop a profitable business model.	1c - Survivability of the startup	When business model is not tested, previous experience and industry knowledge of the founder could play a significant role	Sustainability	New, emerging, business models that could be difficult to convince market
H_6	As risk increases so does the probability of a startup failure.	1c - Survivability of the startup	Technology introduction may create ecosystem risks, and it is important that these risks be addressed to protect venture capital investments.	Sustainability	Startups in existing business areas may have an opportunity to pivot to a different product group. That may not be possible in a new business area
H_{8b}	Where the business model is not proven, the number of press articles provide positive validation of the strength of the business case, and survivability of the startup.	1c - Survivability of the startup	Number of press articles as a signaling stability factor to the market	Sustainability	When business model is not proven, press articles act as signals of positive validation

Survivability / Exit test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_{9c}	Patents would impact the exit and hence is valuable for a venture capital.	1c - Survivability of the startup	Impact of patents on survivability and exit of the startup.	Sustainability	When business model is not proven, patents could help create the unique differentiation and help build revenue
H_{10d}	The presence of trademarks would increase the chances of a startup's survivability.	1c - Survivability of the startup	Trademarks as signals for commercial opportunity	Sustainability	When business model is not proven, trademarks could help create the unique branding differentiation and help build revenue

First funding test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_2	The market size will be a significant decision factor for first funding	2 - Relative importance of other factors $1_{a,\ b}$ - Can machine learning models fit in selecting next stage of funding	The relationship between market size and angel investors has been derived based on interviews and not through a data driven approach. Also, the approach has to be tested for the current negative sentiment market.	Universal - all segments	In first funding, while industry segment plays a role for venture capitals, accelerators tend to be more universal. Angel also chooses their preferred segment
H_7	For angel investors, signals provide positive validation and help with the funding	2 - Relative importance of other factors	Link between signals and first funding	Universal - all segments	In first funding, while industry segment plays a role for venture capitals, accelerators tend to be more universal. Angel also chooses their preferred segment
H_{9a}	For early-stage startups, patents will influence the fundability of a startup.	2- relative importance of patents	Patents as signals for potential commercial activity and hence fund 'ability' of the startup	Universal - all segments	In first funding, while industry segment plays a role for venture capitals, accelerators tend to be more universal. Angel also chooses their preferred segment

First funding test					
Hyp.	**Details**	**Research Questions**	**Gap to be tested**	**Sector**	**Reason**
H_{10a}	If a pre-seed startup has registered a trademark or has live clients, it is more likely to receive funding	2 - Relative importance of other factors	Does trademark provide greater comfort to a first stage funding	Universal - all segments	In first funding, while industry segment plays a role for venture capitals, accelerators tend to be more universal. Angel also chooses their preferred segment

The questions on the hypothesis link with the research questions and target population have been addressed. The following section will focus on the research methods and collection strategies.

Research methods

This thesis aims to explore the possibility of an algorithmic approach fitting venture capital funding and testing for feature significance and venture capital returns. In that context, the study fits a quantitative research practice. However, there are questions to be answered.

1. Is there an element of qualitative research that needs to be included? Quantitative research often indicates the trends, but the context is from qualitative research.
2. How would the results be validated? A practitioner may question the model's validity unless longitudinal or similar test is included.
3. What would the data collection strategy be, and how would that be analyzed in the thesis?

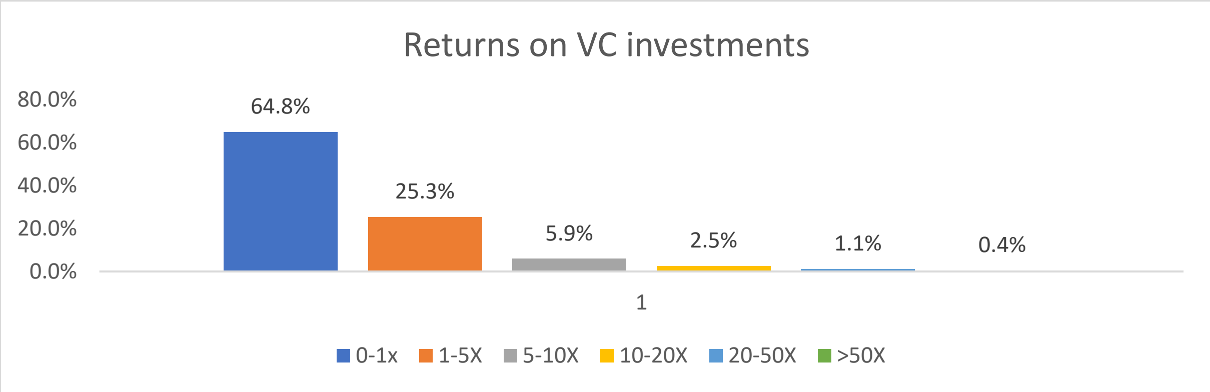
The basic paradigm of the thesis is to explore whether a machine learning model can help venture capitalists with startup funding. The model will be based on multiple features to identify the significant features. This is a quantitative approach where the methods need to be defined. Qualitative commentary would add context where relevant and is recommended for this study as incremental details (Cropley, 2002).

There are multiple ways to interpret the significance of factors identified in the study that lend itself to a mixed method approach. The data and findings could be interpreted based on.

1. Previous theoretical articles can help substantiate that the same insights have been independently drawn, and these correlate with the facts found in this study. But there are theoretical and practical gaps to be studied hence this approach may have limited applicability.
2. By taking a different sample from the same source and validating the findings independently through two different samples, the same features are indicated to be significant. Again, the context can be missing for a researcher to understand. It is not important to only state the numbers unless the thesis can explain the trends and the details.
3. Using qualitative methods to supplement the quantitative methods. The qualitative methods used in this thesis will be applied to the longitudinal study as well as industry context gathered through interactions with multiple practitioners.

The thesis uses a mix of methods. In addition to the data models, a mix of previous theoretical articles and qualitative methods are used for validation. The challenge with data models has been explained in Figure 30 in the comparison between interpretability and accuracy of machine learning methods. Similarly, for qualitative research, the exact method used must be specified. The challenge, of course, is that there are multiple methods, such as case studies, action research, grounded theory, and interviews, among others (Cropley, 2002).

In quantitative analysis, one of the challenges in the startup data is that the data may need to be revised. Figure 1 earlier had shown a skew in distribution. The figure has been repeated below for easy recollection.



The data was checked with Kolmogorov-Smirnoff to test the normality. The test decides whether the sample came from a specified distribution (Chakravarti et al., 1967). The test results enumerated later in the thesis indicated that normal assumption would not fit this distribution. The population was, in effect, non-gaussian.

Non-gaussian refers to a class of probability distributions that deviate from the symmetric and bell-shaped pattern of the normal distribution. Exponential, Poisson, Chi-square, and log-normal are some examples of a non-gaussian distribution. The non-gaussian nature of distribution poses a challenge. As noted earlier in the thesis, regression was the preferred approach in the thesis due to the need for explainability. The standard regression form is ordinary least squares that assume the linearity of data (Fox, 2016), and the linearity of data fits best with a normal distribution.

Ordinary least square is a regression method that fits a plane in a scatter plot of data, assuming the data is linear. While the line may not touch each scatter point, it minimizes the sum of squares of the distance between the fitted regression plane and each scatter point (Fox, 2016). Ordinary least squares method assumes that (i) there is data linearity, i.e., there is a linear relationship between dependent and independent variables (ii) there is independence (no autocorrelation), i.e., two or more variables are not perfectly dependent on each other, and (iii) there is normality. In this case, we know that the data is non-normal and that a different tool is required to analyze the data. Academically, generalized linear model is used to analyze non-normal data.

McCullagh and Nelder (1989) define the generalized linear model as a fit to data based on maximum likelihood. The models were defined to address non-normal distribution and distribution where there is categorical data. In our thesis, we are using data that falls into both these categories. A generalized linear model helps us build a linear model for nonlinear data by using the link function. The link function provides a relationship between the linear predictor and the mean of the distribution function.

The generalized linear model fits well with the data samples and will be used extensively in this thesis. Previous research indicates that generalized linear models have been used for similar studies. Below are a few examples from academic research where they have found acceptance.

1. Cekic and Yildirak (2017) studied the credit scoring of Turkish SMEs, deploying a generalized linear model methodology. Many similarities exist between this study and the thesis. (i) Small sample sizes were used. In the Cekic and Yildirak (2017) study, the sample size was 87, and (ii) the study was focused on risk estimation. The study found that Generalized Additive Models outperform other models for similar studies.
2. Cerchiara et al. (2017) studied the generalized linear model in the context of life insurance actuarial tables. Generalized linear models are usually deployed for general insurance. Cerchiara et al. (2017) recommended that generalized linear models should also be adopted in life insurance. There are a few interesting aspects of this study. (i) Cechiara et al. (2017) backed the quantitative analysis with a case study, and that is what this thesis is also recommending. (ii) the study was in partnership with an industry association and hence could be assumed that it would be relevant to a practitioner, and

(iii) insurance is a risk management business like what we are proposing for startup funding. In insurance, an insurer must decide whether to accept the risk, while in the case of this thesis, a venture capital must decide whether to participate in a funding round. Similarly, David (2015) and Siddiq (2016) have recommended the use of generalized linear models for insurance risk estimations and analysis of the actuarial tables.

3. In the Asian context, Xie and Lawniczak (2021) have proposed that generalized linear models better predict risk-related studies than alternates, such as minimum bias procedures.
4. Elliot and Hsu (2017) deployed multiple models to predict stock time series. While recurrent neural networks performed best, they had a similar challenge of explainability. In the study, generalized linear models performed better than other linear regression models.
5. Grossi and Bellini (1970) similarly deployed generalized linear models to estimate the default probability for small and medium enterprises. The study was around when capital adequacy ratios had been updated in line with Basel II requirements, and the market needed a framework to estimate the risk.
6. Langford (1994) used a Generalized Linear Model on dichotomous choices for the valuation, a model like the one that is deployed in this thesis.

While this is not the complete list, these studies indicate that generalized linear models have been successfully tested for similar industries and similar research questions as those in this study. These previous examples help validate the approach of deploying generalized linear models in this thesis.

In addition to deploying generalized linear models, some of the studies used mixed methods and deployed case studies for validation. Some of the studies had validated the results through practitioners, and some had practitioners as a part of the research team. These methods strengthened the findings, not only helping to provide an additional source of validation but also to ensure that the findings would have a practical application. While the thesis is based on quantitative models, qualitative aspects such as case studies or practical examples have been included in this study to support the data findings. Similarly, longitudinal analysis and discussions with industry professionals provide practical validation.

Lastly, let us focus on possible data collection strategies. There are areas to be covered, as mentioned in the study.

1. Existing startups that have been previously funded (follow-on funding)
2. New startups seeking the first round of funding.
3. Startups in the same industry that have closed.
4. Startups that have successfully exited.

For the purpose of this thesis, survivability and exit have been divided into two different data sets – (3) & (4). This was done as only patents were tested as factors enabling exit while multiple features were tested for survivability. Let us look at each of the segments and the data collected.

Follow on funding.

Four hundred twenty artificial intelligence startups identified from Crunchbase across Europe, the US, and Asia were analyzed to understand the drivers for funding. Of the 420 startups, 137 were Europe-based, 151 were US-based, and 132 were Asia-based. While most variables are continuous, M&A action, patents, and trademarks are categorical variables with binary indicators. Binary categorization of these parameters avoided data errors. This was done as the economic values of patents, trademarks, and previous acquisitions were not defined in the Crunchbase database.

Crunchbase was preferred as a data source. As previously indicated in Table 28, seven of the twelve referenced studies were based on datasets obtained from CrunchBase. Given CrunchBase's acceptance in the academic research world as a data set of integrity, it was considered prudent to rely on the same data set for this thesis.

The top one thousand startups were identified for each region, from Crunchbase and they were scrutinized for outliers. The initial screening criteria used was.

1. Some startups were missing some of the data such as technology build and patents etc. They were screened out.
2. For some startups there was a mix of debt and equity. The startups where debt formed a large part of the funding (>25%) were segregated. Later there is an analysis for European artificial intelligence startups funded partly by debt. Debt funding is usually used for very different business models.
3. Any startup with a zero-funding record was excluded.
4. Only active startups were selected.
5. Boxplots were plotted and outliers that fell outside the limits were removed.
6. From the rest, the intent was to select 125-150 startups at random.

There was only one issue related to Crunchbase. One of the hypotheses relates to the number of employees. Crunchbase usually provides an indicative range such as under 50, 50-100, 100-500, etc. Using mean as an estimate may not be accurate and acceptable. So, a different data source had to be identified for this data. Zoominfo was identified as that data source.

Zoominfo is a go-to-market tool for sales intelligence and is used extensively in practice for B2B sales. Zoominfo provides data on the number of employees, last year's revenue, and company-level contacts. On GetApp, Zoominfo has a rating of 4.2 / 5.0 and is widely used in the sales community. Even if ZoomInfo information is an estimate, the use of a consistent approach and the same platform for all will ensure that there are no data-driven inconsistencies. The data elements considered are listed in Table 32.

Table 32 – Mapping data elements used with hypothesis- follow on funding.

Data Element	Source	Linked Hypothesis	Comments if not linked to a hypothesis
Age of the startup	Crunchbase	None	Historical and practical research has indicated that the investors would ideally exit in 5-7 years (total of angel + venture capital) An investment interest beyond this period could indicate a region-specific behavior.
Number of employees	Zoominfo	Yes	
Number lead investors	Crunchbase	None	Has been a factor in previous research. While the thesis has stated that we do not expect number of lead investors to be significant, it was still tested to confirm the fact that it would be an insignificant factor.
Acquisition prior to funding	Crunchbase	None	Various theories have highlighted the signaling effect of acquisition. The data element was included to measure whether there was a significance of this data element
Articles prior to funding	Crunchbase	Yes	
Number of products in use	Crunchbase	Yes	
Webpage views/visit	Crunchbase	None	This has been used in some previous studies. It was considered not important for this study as the focus is largely on B2B in the AI sector, whereas page views/visits could be important for the B2C sector.
Patents	Crunchbase		
Trademarks	Crunchbase		

A brief discussion on acquisitions prior to funding and web page views/visits is required at this stage as these two data elements have been included, and a reader may contemplate their significance.

Entrepreneurs acquire other companies for either growth or access to specialized resources such as innovation or talent. Various authors have covered this in detail. On growth, DePamphilis (2001) and Burger et al. (2023). These are just two of the works in this scholarship that have much written on them from both an academic and practitioner perspective. DePamphilis (2001) published a case study of an actual acquisition in the CD-ROM market that was completed to drive growth. Burger et al. (2023), a recent work, has been highlighted as this is one of the few works that has studied the impact of acquisition on growth and innovation in high-technology industries. A recent National Bureau of Economic Research paper (Jin et al., 2023) has also indicated that the acquisition of a high-technology startup can help the incumbent leap from the market. Similar studies, based on M&As of startups with a US patent, have indicated such acquisitions may help the acquirer.

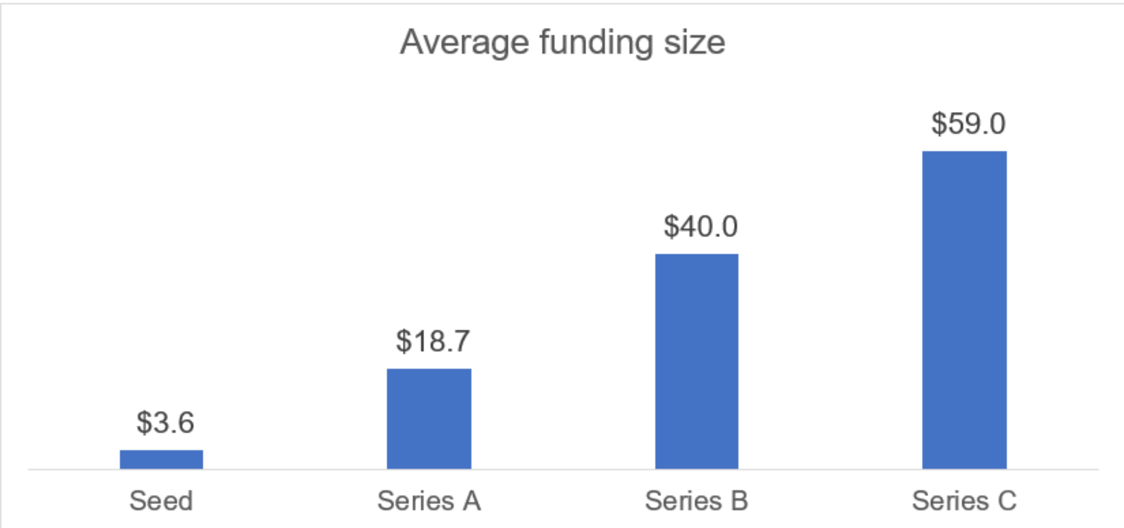
There are three main reasons why acquisitions were not included as a factor.

1. Acquisitions play a similar role as press articles. They can be used as signals. For acquisitions they usually indicate a pivot to faster growth and an optimism in the startup. They are expected to behave like the signal's discussion earlier; hence, they are omitted.
2. Acquisitions could be for a mix of reasons, such as signaling mentioned earlier, growth, or to acquire patents. It could be significant as a cross product variable but may not be significant by itself unless the other signaling variables are not effective.

3. As stated in the work of Burak (2023) mentioned earlier in the discussion of angel investors, product mix, and funding sources., acquisitions are sometimes used for new product introduction in the late stages of a startup (Series C and above).
4. Qualitative aspects related to the acquisition could not be verified. While the name of the acquired company was known from Crunchbase, investors would be keen on much more data such as value the new acquisition can bring to the startup, and the deal price.

The second variable not included in the hypothesis is the age of the startup. Historically, the funding of a startup follows the following sequence. The average rounds per stage are in Figure 33 below.

Figure 33 – Average rounds per stage.



Source: Crunchbase (2023)

It should be a surprise if the late stage does not lead to higher funding, as that would indicate structural issues with the funding market or that firms are raising money very late in the aging cycle. Either way, it may not fit well with the innovation and economic growth drive.

One of the reasons late-stage was included as a factor of testing was that it denotes the expansion stage where the innovation starts getting absorbed in the mainstream. Not only that, but this would also typically be the stage where venture capitalists would start anticipating a return. That is the reason that it was important to confirm that late stage was a significant factor for both funding as well as venture capital efficiency and returns.

In addition to these and the other data elements, cross-product interactions were also tested to understand the interactions between various factors. The details analysis will be discussed in the findings and analysis section.

Startups seeking first funding.

Jan'22 was when the startup market first indicated that the sentiment was changing, and it would be more difficult for first time founders to fundraise. First fund raise is an important use case in this thesis. Its importance increased as it was now also being pivoted towards helping entrepreneurs fundraise.

Usually, the data of startups seeking their first funding can only be found in two places: (i) for the US market, where data on crowdfunding is found in the EDGAR database, and (ii) with early-stage funds and accelerators. Data of fifty first funding requests were shared for this thesis. In this thesis, we have experimented with both data sources. Crunchbase was not selected as a dataset source while it has data on pre-seed startups. Of the 1000 samples considered, 83.7% had been funded at least once. That would make the data unsuitable for this thesis.

The second part was run as an experiment with a US-based early-stage funding facilitator. In this context, the masked data was shared, and that was embellished to run a data model. The intent was to check whether data recommendation in the pre-seed stage was comparable with the recommendation from a full investment committee. The total data considered in this study was as follows. The data elements used are mentioned in Table 34.

Table 34 – Data elements used for pre-seed / first-round funding.

Data Element	Source	Linked Hypothesis	Comments if not linked to a hypothesis
Number of co-founders	Partner	None	Usually, first-stage funding partners only fund startups with a co-founder, as a single founder has historically been risky. This data was used as categorical data.
Founder details	Partner, LinkedIn	Yes	
Investor count (used as a proxy for lead investors – interest)	Partner	None	Usually, for first funding stage, investor count is a signal for angel investors (Conti et al., 2023). The data was included to test signals as a factor.
Product count	Partner	Yes	
Patents	USPTO	Yes	
Trademarks	USPTO	Yes	
Market Size	Statista	Yes	
Number of employees	Zoominfo	Yes	
Press articles	Crunchbase	Yes	

The data included the startups details, its country of origination, and details about its current traction, business model, and product group. Based on the founder and co-founder details, their previous experience, education, and other details had to be collected out of LinkedIn. Further some data had to be independently validated as founders' integrity is known to be suspect on these. This is:

1. Market size and growth. Since most founders are aware that market size is a critical data element, it tends to be exaggerated in the pitch decks and funding asks. For this

study, the TAM (total addressable market) was independently validated using reputed third-party research sites such as Statista and GlobalMarkets.

2. Patents – usually startup founders report it once they have filed for it. US Patents and Trademarks Office database was checked to verify the authenticity of the reporting.

Some integrity issues were found in the founders self-reporting, and these were summarized for the early funding facilitator.

The funding at this stage will be considered angel investor funding as the funding facilitator would introduce these startups to their network of angels. For these to be successfully funded, the startups should meet the preferred criteria for angel investor funding as identified in Table 24. Unfortunately, there were gaps that were aligned with the hypothesis that the first funding would be a mix of data and human decisions. These gaps are mentioned in Table 35.

Table 35 – Missing data factors for the first funding.

Pillar of Decision-Making	Decision points identified in Table 24	Is the data available
Product	Is it of personal interest	X
	Is it protectable	Y
	Is it innovative	X
Market	What is the Market Size	Y
	What is the growth potential?	Y
	Customer engagement	Y
	Market dynamics/competition	Y
Entrepreneur	Industry Experience	Y
	Track record	Y
	Passion / Commitment	X
	Integrity	X
	Technology Use & Knowledge	X
Financials	Profitable/ Realistic Plan	X
	Capitalization/ Cash Flow estimates	X
	Size of investment	X
	ROI / Valuation	Y
Investment	Team characteristics	Y
	Business Fit (Market / Structure)	Y
	Location	X
	Referral/ Co-investment	X

Only half the factors were available, and the rest were unavailable for the study. The available factors would necessitate a partial analysis of data, and only the factors that were considered necessary would be checked for significance. Hence, a different technique was deployed of a data driven acceptance model and traditional investment council together deciding on the startups to be funded. This aspect was also mentioned briefly earlier in the thesis and will be covered in detail in the later parts.

One of the questions by a reader can be on why Electronic Data Gathering Analysis, and Retrieval Site (EDGAR) data was not used as a data source. Since 2016, data for all crowdfunding campaigns run on approved crowdfunding sites must be stored in EDGAR. EDGAR is managed by Securities and Exchange Commission (SEC). While data is available on EDGAR for crowdfunding, it was not usable due to the following reasons.

1. The same startup could go through multiple crowdfunding rounds. While the funding may fail initially, it could receive the funds in the follow-on rounds without a material information change. E.g., a startup set up a campaign to raise funds with a crowdfunding platform, but the campaign failed. The same startup, with the same information, raised the request a second and a third time and was crowdfunded in the third attempt.
2. The funding received could be a mix of equity, debt, or SAFE (a simple agreement for future equity where future raise rounds would determine the equity price). Investors usually prefer debt for restaurants and food businesses. In the thesis we focus on risky equity as a funding source.
3. The mix of industries found in EDGAR data is counter-factual to the central paradigm of this thesis, innovation as an enabler for economic growth with the growth facilitated by venture capital. In the thesis, the focus is on high technology startups.
4. The crowdfunding investment model is different. Angel investors usually invest US $25k + in a startup and accelerators US $100k+. On a crowdfunding site, the minimum cheque size could be as low as $ 1,000. That is probably the reason why syndication usually works on crowdfunding site as investors may not be conducting full due diligence. Crowdfunding needs a different form of feature selection.

5. The thesis findings must be relevant to both academicians and practitioners. A joint funding exercise with an early-stage accelerator is a practitioner validation while testing of the identified gaps ensures an academic relevance.

Hence, the EDGAR data was not used. Next, we consider sustainability data used in the thesis for the purposes of categorical prediction of whether a startup will survive. Survivability is critical for venture capitalists returns and central to the funding efficiency paradigm of this thesis. *Survivability of a startup.*

Crunchbase data on sustainability formed the basis of this analysis. Sustainability, as mentioned earlier, was chosen as a field where business models are still fluid. Many scholars have suggested that sustainability business models are evolving and need co-evolution to succeed (Schalteggar et al.,2016; Najmaei & Sadeghinejad, 2022). Co-evolution necessitates a sharper focus on due diligence.

Sustainability is also a focus in economies, as sustainable growth ensures a future. As climate change has reminded us repeatedly, we are living amid a tumultuous time, and it is in the interest of economic development to focus on sustainability. As mentioned earlier in the thesis, it is also a sector with the top venture capitalist investment in 2023. Sustainability was considered a sector of interest mainly due to this reason.

To select the data set, top data of 1,000 sustainability startups, both closed and active, were selected. The data was then scrubbed to finalize the sample. Box plots were drawn, and outliers were excluded. Crunchbase was used as the dataset source for the reasons:

1. It was previously used for similar studies by different scholars.

2. The intent was to choose startups that had received at least one round of funding from a venture capital. The intent is to verify whether the venture capital investment is safe from an early closure.

Of the sample collected, 196 sustainability startups were drawn randomly, of which 91 were active and 105 were closed startups. The data was selected to ensure that active and closed startup numbers were balanced and almost similar in the test sample. The selected data elements are included in Table 36.

Table 36 – Data elements for the test of survivability

Data Element	Source	Linked Hypothesis	Comments if not linked to a hypothesis
Industry characteristics	Crunchbase	None	A new test variable that was not linked to any previous research. The data was segregated into two main categories - renewable energy & all other sustainable projects. The segregation was initiated as energy projects usually require a significant upfront capital.
Customer traction	Company website	None	Whether the funded startup is pre revenue or post revenue
Risk	Crunchbase	Yes	
Market size and growth	Statista	Yes	
last funding type	Crunchbase	None	Checking whether funding other than equity funding affects the chances of survival. Our paradigm is that VCs are funding through equity investments
Number of employees	Zoominfo	Yes	
Founders profile	LinkedIn	Yes	
Signals	Crunchbase	Yes	
No of lead investors	Crunchbase	Yes	
Patent	Crunchbase	Yes	
Trademark	Crunchbase	Yes	
Technology stack	Crunchbase	Yes	

The industry characteristics must be mentioned as a variable included in this thesis. Practitioners have focused on it for a long time, and so have angel investors. Yet, it has often been overlooked in the other research. There have been recent articles that have covered it, Kim et al. (2023) recently wrote about it to test it as a funding driver. No similar research was found from a survivability perspective.

As mentioned earlier, since this thesis is designed to contribute to both academic and practical world, the tests are industry specific except for the first funding. A quick visit to any of the venture capital websites would reveal a tab called “investment thesis.” Investment thesis usually states the industries the fund invests in, and the stage where it starts investing. The structure of this thesis with first funding and follow-on funding mirrors what a reader may find on a venture capitalist site.

The last test was whether patents help in a successful exit. The data used for this test was the same that was extracted to test follow-on funding, and only the US data was used. Next, we analyze the data and cover the finding and their implications.

Findings from the analysis

Having built the case for a data-driven approach toward venture capital funding, it is now imperative that we verify whether the identified gaps can be tested with actual startup data. Again, this would need to include testing whether a venture capital may be able to generate return or increase the predictability of the investment.

As discussed in the previous sections, there are really four scenarios to be checked. These four scenarios cover the entire lifecycle of the startup, from its first funding to its eventual exit. Four different data checks were conducted, and as discussed in the previous section, four data sets were prepared to be tested. This section will present the test findings and discuss their implications. The desired result is an improvement in venture capital funding efficiency, as this can impact wider economic development. The results are positive and indicate an improvement opportunity. The result details are enclosed.

Follow-up funding data analysis.

Follow-up funding is central to our thesis and its main business case for the following reasons.

1. The first funding by venture capital is usually at a seed stage after the startup has been funded by either angel investors, an incubator/accelerator, or through friends and family. In rare cases, venture capital funds the first round.
2. The funding amount increases with every round, and losses arising from late-stage funding could be significant. Consider the following example from a recent exit in Table 37.

Table 37 – Returns on InstaCart at IPO

		Compound Annual Growth Rate		
VC Round	**Year**	**Investment v/s IPO**	**S&P 500 (same period)**	**Return v/s S&P 500**
Seed	2012	55.02%	13.04%	41.98%
Series A	2013	61.96%	11.28%	50.68%
Series B	2014	29.16%	11.04%	18.12%
Series C	2015	10.60%	12.31%	-1.71%
Series D	2017	8.26%	12.39%	-4.13%
Series E	2018	8.19%	10.92%	-2.73%
Series F	2018	0.05%	14.22%	-14.17%
Series G	2020	-14.74%	7.88%	-22.62%
Series H	2020	-20.80%	-1.14%	-19.66%
Series I	2021	-51.17%	19.20%	-70.37%

Source: Damodaran (2023)

Only some rounds have a high return. This table also validated the main paradigm in this thesis. Every round needs its own due diligence to ensure venture capital funding efficiency. The thesis is proposing that a data model can provide a due diligence framework per round, and it can indicate to an investor as to when it should restrict investments in a startup. This would be tested later in this section. The test is important as in the context of Instacart only investors till Series C made money. Rest either had returns less than S&P 500 for a much higher risk asset, or lost money.

The recent private market slowdown has affected the latest rounds of funding and investors would have lost money as the valuation of the latest round of funding would have been much higher. This example highlights the importance of gauging the readiness for follow-up funding and risk at every funding stage. The funding efficiency cannot be improved unless the follow-on funding is optimized.

A generalized linear model is used to validate that a data model. As mentioned previously, 420 artificial intelligence startups from Crunchbase across Europe, the US, and Asia were analyzed to understand the drivers for follow-up funding. Of the 420 startups, 137 were Europe-based, 151 were US-based, and 132 were Asia-based. The model was run on Python. The representative data for these can be found in Table 38.

Table 38 – Descriptive statistics of the artificial intelligence startup samples chosen.

Data Element	Asia	Europe	USA
Observations (#n)	**132**	**137**	**151**
Average funding amount (US$ Million)	27	36	108
%age classified as within late stage of funding	38%	41%	72%
Average number of employees	203	161	261
Average number of lead investors	3.4	2.8	4.1
%age that acquired others prior to the last round of funding	6%	17%	27%
Average number of articles prior to the last round of funding	15.8	27.4	75.7
Average number of tech products in use	16.7	27.2	42.2
Average number of webpage views/visit	3.6	2.6	2.6
%age of startups with patents	31%	26%	53%
%age of startups with trademarks	24%	74%	76%

A generalized linear model test was run on these three datasets on the factors and their significance for funding. The summary of findings is included in Table 39.

Table 39 – Generalized linear model results.

Data Element	Linked Hypothesis	Asia			Europe			USA		
		Coefficient	p>|z|	VIF	Coefficient	p>|z|	VIF	Coefficient	p>|z|	VIF
Direct factors										
Late Stage	-	20.13	0.000	1.70	16.77	0.001	2.30	69.85	0.000	4.98
#of employees	H_1	53.00	0.000	1.93	51.76	0.000	2.65	58.23	0.000	2.47
# of lead investors	H_2	Not significant			Not significant			Not significant		
Acquisition prior to funding	-	Not significant			Not significant			58.42	0.000	**7.16**
Articles	H_9	11.06	0.013	1.74	9.68	0.025	2.92	Not significant		
Technology products	H_5	Not significant			Not significant			Not significant		
Webpage views/visit	H_5	Not significant			Not significant			Not significant		
Patents	H_{12}, H_{14}	19.49	0.000	3.46	17.95	0.012	3.11	Not significant		
Trademarks	H_{17}	Not significant			11.03	0.004	3.22	19.02	0.016	4.98
Cross-product factors										
Acquisitions: Articles	-	129.87	0.006	**8.92**	72.68	0.004	**6.57**	Not significant		
Patents: Trademarks	H_{16}	Not significant			Not significant			Not significant		
Acquisitions: Late Stage	-	-42.66	0.000	4.16	-39.88	0.032	4.60	-44.71	0.009	**5.62**
Articles: Patent	-	Not significant			Not significant			Not significant		
Acquisitions: Patents	-	-73.86	0.000	4.16	Not significant			Not significant		

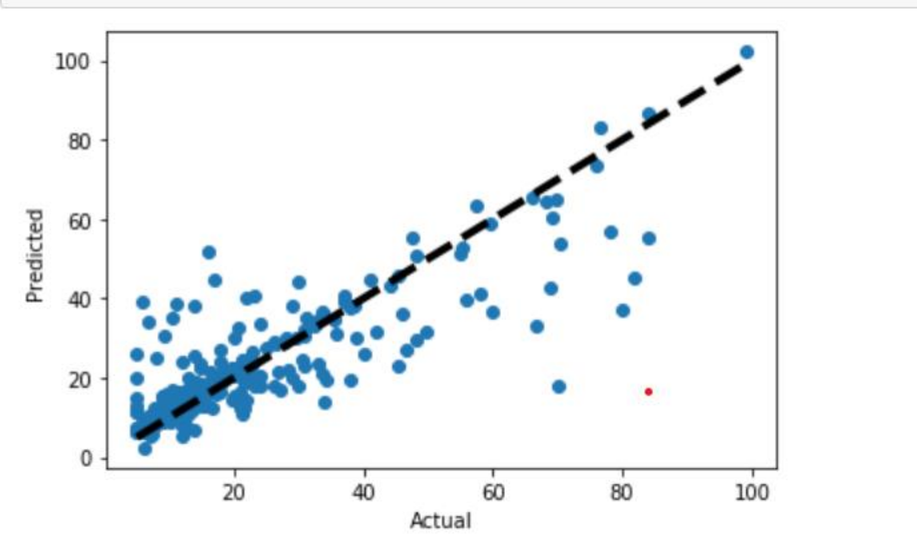
The paradigm is not just that certain factors could be significant but that a data model is possible. While factor significance is the first step, a data model needs more than factor significance. As mentioned earlier, the thesis will only elaborate on funding factors and not models. Each venture capitalist may decide to customize own model based on their factor and investment thesis significance. The art of possible is further validated by the fact that the predictions in this thesis have been based on machine learning models defined for the purpose of this study, and they have generated accurate predictions. As mentioned above, the validations in this thesis are based on.

1. The factors were converted into a machine-learning model and used for prediction. The same model was also applied longitudinally to validate the findings.
2. In our study, we have focused on artificial intelligence as a startup business segment and identified certain significant factors The same factors were tested for one other business segment and the test results highlighted to indicate that the data models need to be industry specific; similar to what this thesis has stressed.

The first test was conducted on a combined sample of Asian and European artificial intelligence startups. Both these startups have similar characteristics as can be inferred from the data analytics finding in Table 38 and Table 39. In Table 38, Asian and European artificial intelligence startups selected in the sample are similar in characteristics. The percentage of late-stage startups and other data elements are similar. The startup sample is largely for early-stage. In Table 39, the two startup samples behave almost similarly, and similar direct and cross product effects have significance. To test the theory, only the early-stage startups were selected. The total early-stage startups in the base were 233 (Europe + Asia).

For these 233 startups, a prediction model was built to predict the level of funding based on the data elements, and the results of actual funding and predicted funding were mapped into a graph. The graph is attached below as Figure 40.

Figure-40 – Mapping of actual v/s predicted funding level



The model indicated interesting facts. If predicted funding is compared to actual funding and normalized, the results show that majority of the data is within standard errors, but with a high variance as measured by standard deviation. A similar model was run on revenue generated by the same startups that showed a much closer variance and a more balanced trend. The details are in Table 41 below.

Table-41 – Model statistics

Test area	Mean	Standard deviation (SD)	Within +- 1.96 SD	> 1.96 SD	<1.96SD
Funding $_{Actual}$ - Funding $_{Prediction}$	$1.2M	$53.2M	221	12	
Revenue $_{Actual}$ – Revenue $_{Prediction}$	-$0.13M	$10.3M	216	9	8

Based on the model, there is a 5-10% opportunity to improve venture capital funding efficiency. The 5-10% efficiency improvements in a US$ 400 Billion funding bucket would translate into loss avoidance of around US $ 15- 25 billion on follow-on funding. The actual figures for a venture capitalist may vary based on their thesis and industries invested. Also, the models would improve with learning.

To validate the model, longitudinal analysis was conducted. For this thesis, the model was validated over a period of one year, i.e., the predictions were made in June'2021, and they were revised in August 2022 to check for their authenticity. Usually, as indicated earlier, in the data set, the startups were raising funding every 1,5 years so 1 year was considered adequate to check for the funding efficiency. Below is the summary of results in Table 42, seen for the predictions.

Table 42 – veracity of the prediction decision.

Total sample size	To be designed	Numbers	Accuracy after a year	Accuracy %age	Exits seen	Business expansion
233	Fund	34	28	82%	5	17
	Do not fund	33	26	76%	1	7

These results are important as they indicate that it may be possible for a venture capital to gauge the follow-on funding readiness. While it could be stated that one year is not a long enough timeline to gauge a startup, the prediction is for this funding round. Usually, a startup raises a funding round every 1.5 years. In the data of the US artificial intelligence startups, startups without patents were fundraising every 1.6 years and those with patent were fundraising every 2.1 year.

The funding prediction needs to be valid for around 1.5 years as after that, the risk changes.

In the second part, we studied the significance of the same factors on funding of fintech startups. Below is the summary of results in Table 43.

Table 43 – Comparison of importance of factors for funding. AI Startups and Fintech startups

	Asia		Europe		USA	
Data Element	AI startups	Fintech startups	AI startups	Fintech startups	AI startups	Fintech startups
Direct factors						
Late Stage	Significant	Significant	Significant	Significant	Significant	Significant
#of employees	Significant	Significant	Significant	Significant	Significant	Significant
# of lead investors	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant
Acquisition prior to funding	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant
Articles	Significant	Significant	Significant	Not significant	Not significant	Not significant
Patents	Significant	Significant	Significant	Not significant	Not significant	Not significant
Trademarks	Not significant	Not significant	Significant	Not significant	Significant	Not significant
Cross product factors						
Acquisitions: Articles	Not significant	Not significant	Not significant	Not significant	Not significant	Significant
Patents: Trademarks	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant
Acquisitions: Late Stage	Significant	Not significant	Significant	Not significant	Not significant	Not significant
Articles: Patent	Not significant	Not significant	Not significant	Not significant	Not significant	Not significant
Acquisitions: Patents	Significant	Significant	Not significant	Significant	Not significant	Significant

Only Asia seems to have the same factors across fintech and artificial intelligence that are significant for venture capital funding, whereas, in the case of Europe and the US, many of the factors vary. i.e., the factors that could have a significant influence on funding in artificial intelligence may not be considered important for fintech startup funding. In Asia, most of the fintech startups also deploy artificial intelligence technologies; and the artificial intelligence market is yet to mature to deeper tech.

Next, let us analyze the results as to why these factors are significant for venture capital firms' funding of artificial intelligence startups.

Analysis of factor significance results – follow on funding.

The discussion in this section will focus on the twelve factors tested. These include the direct factors of impact of late stage, the number of employees, the number of lead investors, the number of articles prior to funding, technology product development, the impact of patents, and the impact of trademarks. The significance of the following cross products will also be discussed. These include the significance of acquisition prior to funding and articles, patents and trademarks, acquisitions in the late stage, impact of articles on patents, and impact of acquisition and patents. The discussion will include the regional differences and views from both the practical and academic worlds.

Impact of late-stage follow-up funding of an artificial intelligence startup by a venture capitalist.

This factor is central to the funding of a startup and, hence, was not tested through a hypothesis. The central belief is that funding would increase with the stage of the startup. As expected, the results showed that late stage was a significant factor in all three regions. Regression coefficient was highest in the US.

This was discussed briefly in the earlier sections of the thesis, with Figure 9 denoting the impact of the late stage on the overall venture capital results and Figure 23 denoting the link between funding stages and the median raise. The two figures are enclosed for easy reference.

Figure 11- The need for risky capital in a Startup. The initial cash flows are negative.

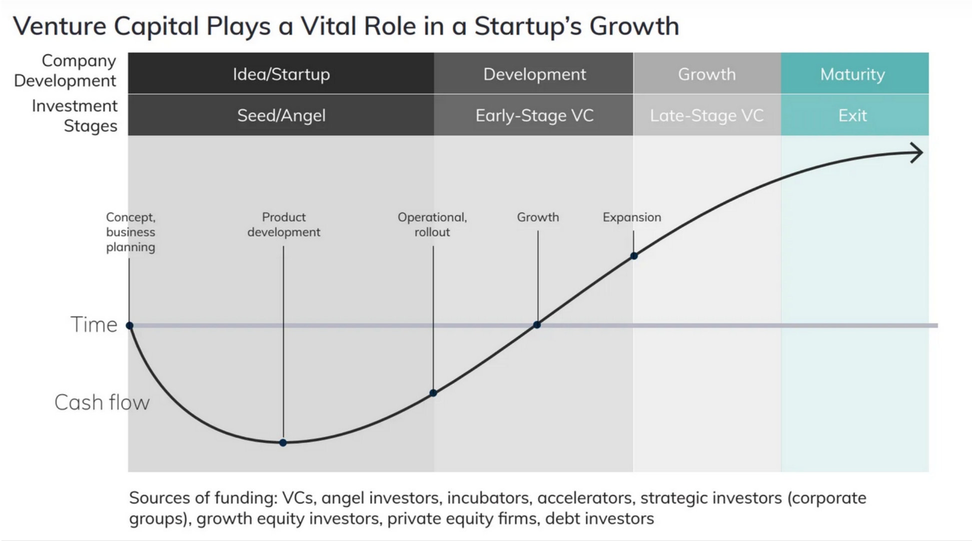
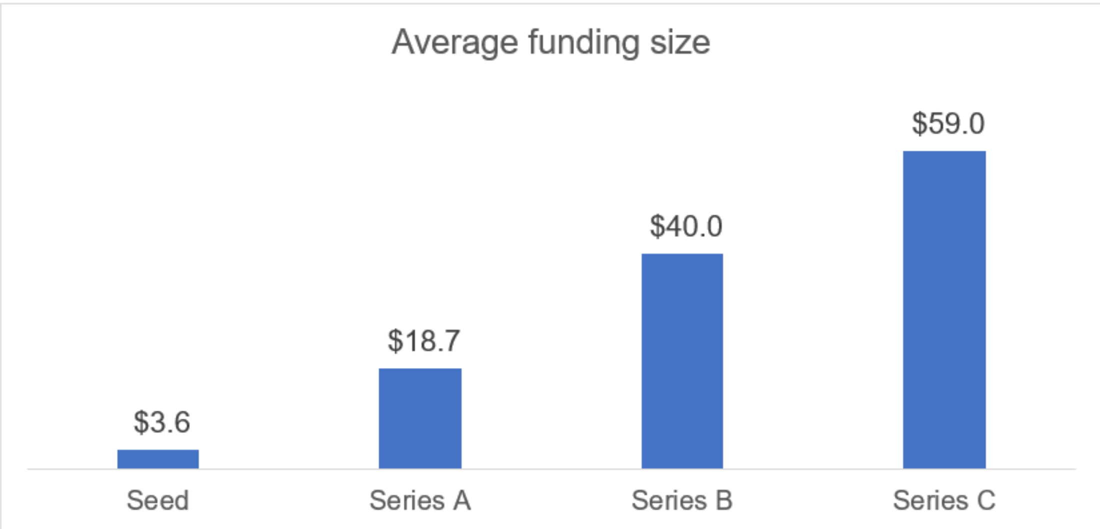


Figure 32 – Average rounds per stage.



Source: Crunchbase (2023)

Based on these two figures, late-stage funding is critical to exit planning and venture capital returns. At the same time, since the startup is expanding, it will need more funds. All three regions have indicated that late-stage growth would be a significant driver for funding which implies that all three regions have healthy artificial intelligence startups.

Earlier in the thesis, a panel discussion on fintech resiliency was mentioned where the standard argument by a partner in a leading private equity fund was that "there is real money for real problems." These artificial intelligence startups would fall into the same category.

While additional funding was expected in the late stages, the generalized linear model has raised two important aspects that need discussion. (i) the coefficient of significance of the late-stage artificial intelligence startups varies considerably by region, and (ii) the coefficient of cross product between late-stage and acquisition is negative across all three regions.

A higher coefficient for late-stage funding in the US market is expected due to the underlying dynamics of the venture capital market. As per Crunchbase (2023), $ 39.2 billion was invested in Q1'23 in late-stage startups globally. Of this $39.2 Billion, the US alone accounted for $27.2 billion, whereas Asia was $ 7.0 billion. The other finding of the negative coefficient of acquisition and late stage for an artificial intelligence startup requires a deep dive.

The impact of mergers and acquisitions on startups and corporates has been discussed and debated. We recommend it as a possible exit strategy for startups, especially when an incumbent is acquiring the startup. The same may not apply to same-size corporates or startups acquiring other startups. When a startup gets acquired by an incumbent, the innovation produced by the startup is more likely to be diffused in the economy. For corporations of similar size, the theory suggests that value destruction is probable.

The probability of marginal value creation has been shared by Demirer and Karduman (2022) and Borodin et al. (2020), among other scholars. Many scholars view it as a double-edged sword. Borodin et al. (2020) studied the impact of M&A on 138 large US and European companies and could not find a significant correlation between M&A and financial performance. The return on sales deteriorated slightly. Demirer and Karduman (2022), in a paper published for the Federal Trade Commission (FTC) USA, found a 4% productivity increase. Based on the venture capital returns distribution, a venture capitalist would typically want a chance for a 10X return. Acquisitions with a 4% productivity gain would not tick the box; hence, we cannot see a direct correlation between acquisition and funding increase. The coefficient is negative.

The impact of acquisitions on funding and valuation should ideally be a topic for further research. Many startups are deploying this as a technique for expansion. A recent data pulls from Crunchbase of 390 global startups indicated that 166 had acquired other startups with a total of 361 acquisitions. The reason for negative returns could be of interest to both the entrepreneurs and venture capitalists.

Impact of the number of employees on follow-up funding of an artificial intelligence startup by venture capital.

The impact of the number of employees on the funding of artificial intelligence by a venture capitalist has been included as a hypothesis.

H_1 – For similar industry segments, the number of employees will be a significant factor in the follow-on funding.

Based on the significant results derived from the generalized linear model and $(p>|z|) < 0.05$, we fail to reject H_1 that the number of employees does impact the funding level of an artificial intelligence startup. Furthermore, let's compare the results from the three regions of Asia, the US, and Europe. We see a similar coefficient value indicating that venture capitalists across the regions hold a similar significance for this factor for follow-on funding, and one of the assumptions is that the founder team would build a delivery team once they receive their first funding.

This finding has a significant implication for both venture capitalist and the founders. Venture capitalist, especially in a high technology area like artificial intelligence, need to realize that the startup needs to be scaled, and scaling requires resources. Most of high-tech founders tend to be technologists who are enamored with the latest technology in the market and the product development cycle. Commercial, organizational development skills are needed. That is the reason Wasserman (2014) states that by year 3, 50% of the startup CEOs no longer have the corner office.

Impact of the number of lead investors on follow on funding of an artificial intelligence startup by venture capital.

The impact of the number of lead investors on a venture capitalist's follow-on funding of artificial intelligence has been included in the test. As discussed earlier in the thesis, we expect lead investors to play a role in crowdfunding, but the role may not be significant for venture capital follow-on funding. Based on the results of the generalized linear model the number of lead investors does not influence the follow-on funding.

Impact of the number of articles on the follow-on funding of an artificial intelligence startup by a venture capitalist.

In the thesis, the number of articles was used to measure signals and determine whether signals significantly influence venture capital funding. It must be added that press articles are one form of a signal, and there can be other forms. For this thesis, the hypothesis to be tested was.

H_{8a} – For venture capital-funded startups seeking further funding, the number of press articles helps provide positive validation for funding.

Based on the generalized linear model results, for the thesis failed to reject the hypothesis for Asia and Europe but must be rejected for the US. We must state that the rejection is because the number of articles prior to funding was not found to be significant, and the rejection of the hypothesis may not extend to the correlation between signals and funding. That must be separately tested, and that could be an area of further research.

The US dataset behaves differently from the European and Asian artificial intelligence startups. There could be multiple reasons for this.

1. Asian and European startups seem to be at an earlier stage than US startups. The data sets for Asian and European startups have approximately 40% as late stage, whereas the US has 72% of the startups in the late stage.
    a. Signals as funding factors could potentially be important for earlier stages of funding and not for the later stages. That could be a potential research area for the future.
2. In the US, the better startups have multiple avenues of being covered by the press, and the same may not apply to the Asian and European startups. E.g., in the datasets identified, a US artificial intelligence startup was in the press 75.7 times on average. In contrast, an Asian artificial intelligence startup featured 15.8 times on average, and a European artificial intelligence startup featured 27.4 times on average. However, there is

a link (though the generalized linear model has not found significance) based on the following.

  a. The US artificial intelligence startups with greater than 100 press coverage were able to raise US$200 million, whereas the other startups raised an average of US$ 126 million.

3. The US tends to be more on social media, so the entire coverage and sentiment analysis of signals on social media could be important.

As an interesting iteration that was not included in the analysis, the press articles were gauged by a sentiment analysis software. That showed a consistent result where startups with positive sentiments were closely correlated to funding. The data sample was not large enough and it included different industry types, hence the results are not being published in this thesis. It is best that this should be studied independently. The independent study would help the entrepreneurs more than venture capitalists though. Entrepreneurs need to understand where to focus their marketing efforts, a media mix analysis could be helpful for them.

Impact of technology product build on follow on funding of an artificial intelligence startup by a venture capitalist.

Recently, Microsoft's investment in OpenAI has been in the news, and in December 2023, Google launched its updated large language model, Gemini. Both these news significantly impacted the underlying stock price of Microsoft and Google. Given these, technology, incredibly unique technology innovation, would significantly impact the valuation and stock price. That is what the previous research suggests (Emir Hidayat et al., 2022; Hyytinen et al., 2015).

Emir Hidayat et al. (2022) and Hyytinen et al. (2015) have both suggested that cutting-edge technology would increase the attractiveness of the startup. Cutting-edge technology can be measured through patents or, in some cases, especially in software, by unique software that may not be patented. The challenge in this thesis is that it is difficult to estimate the unique software and to build a metric to measure it. For that purpose, the two metrics identified from Crunchbase were.

1. The number of technology products in use.
2. Number of unique visitors to the website/ month

The thinking was that the number of technology products would be a proxy for B2B businesses, and the number of unique visitors on the website/month would be a proxy for B2C businesses. Hence, the hypothesis to be tested was:

H_4 – The number of software applications a startup develops will be positively correlated with VC funding raised.

The null. The hypothesis must be rejected. The generalized linear model could not find significance between these metrics and funds raised. This could again be a topic for further research as the right metric to measure must be identified.

Impact of patents on funding of an artificial intelligence startup by a venture capitalist.

Patents are the crux of this thesis. It links well with the paradigm that patents are an indicator of innovation, and innovation helps build economic growth. All innovations in the initial stages could be considered risky, and hence, funding innovation requires a venture capital ecosystem as it can absorb risky investments; hence, this thesis focuses on the importance of factors as probable measures to improve venture capital efficiency.

While we deep dive into patents, there are a few things to note.

1. Patent regulations vary by region. Also, while the US and Europe are considered a single market for the issuance of patents, patents must be applied by Asian countries.
2. Patents do not automatically help a startup generate revenues. As indicated in previous research, AI startups are challenged in the commercialization of patents (Halle et al., 2014).
3. From a practice standpoint, often for university and high technology startups, the founders file for a patent and then apply for funding to build a commercial enterprise on the back of the innovation.
4. Patents are not that readily available for software-based industries as methods, in some cases, are considered nonpatentable. The United States Patents and Trademarks Office (USPTO, 2016) allows only software that transforms an abstract idea into a practical application to be patented.
5. Patents in practical applications are found to be significant for earlier stages of the startup when looking for new investors; they lose some of their significance in the late stages but are again significant during exit.

Three hypotheses were identified in this thesis. These are.

H_{9b} – *Where the startups have been funded once, patents would be important factors influencing funding efficiency.*

H_{9d} – *There are regional differences in the importance and impact of patents as funding factors.*

H_{10b}– *The combination of patents and trademarks should influence a venture capital funding decision.*

For H_{9b} – *Where the startups have been funded once, patents would be important factors influencing funding*. The hypothesis cannot be rejected for Asia and Europe, For the US, the hypothesis must be rejected. There are multiple reasons that the US behaves differently.

1. If we review the datasets carefully, the artificial intelligence startups are at an earlier stage for Asia and Europe than the US-based dataset. It could signify that the practical knowledge of "Patents in practical applications are found to be significant for earlier stages of the startup when looking for new investors, they lose some of their significance in the late stages but are again significant during exit" has merit. This seems is in line with the findings of Hsu and Ziedonis (2006), who suggested that startups invest in patents in the early stage, as that is when they can effectively act as a signal to attract funding.Ofcourse, from a venture capitalists efficiency perspective, patents as signals alone is not a preferred outcome as the impact should be on commercialization instead.
2. In the data sets, for Asia and Europe artificial intelligence startups, 31% and 26% have registered a patent. In the US dataset, over half of the startups (53%) have registered patents. Previously, we had discussed that Graham et al. (2002) considered the patents for similar inventions in both the European Patent Office (EPO) and The US Patents and Trademark Office (USPTO). On average, a valuable patent was challenged thirty times more in EPO than in USPTO. Each challenge is important, as 41% of the challenges are successful. Based on this, there are regional differences; hence, the venture capital may not accord the same importance to these patents.
3. In the later sections of the thesis, it will be proven that patents help with exit.

The challenge in the US is around the regional differences and approval process of patents and the age when the patent is acquired. 76 US artificial intelligence startups with 1,517 patents were studied to identify when the startup acquired the patents. The dates were from the USPTO site. The results are in Table 44

Figure 44 – Vintage US patents issued for artificial intelligence startups.

	Number	**%age**
A total number of artificial intelligence startups with patents considered.	76	
Acquired patents in less than one year of incorporation	3	4%
Acquired patent within 1-5 years of being incorporated	49	64%
Acquired patent after > 5 years of incorporation	24	32%

Source: USPTO (2022)

Usually, if there is significant new information, venture capitalists will only be interested in a >5-year company from the perspective of exit planning. They may not be considered useful. In this context, Hall (2006) interviewed 351 managers who received seed funding and found that 30% had valuable patents, and 10% had patents that Hall (2006) classified as not that valuable. The same would apply to the later stages of funding.

Next, we review the following H_{9d} – *There are regional differences in the importance and impact of patents as funding factors.* we fail to reject the hypothesis with similarities in Asia and Europe and differences in the US.

Finally, we review H_{10b} – *The combination of patents and trademarks should influence a venture capital funding decision.* For this hypothesis, analysis was conducted across both a cross product of patents and trademarks as a significant influence over funding as well as whether it helps drive revenues. A significant amount of data was tested to check this hypothesis.

The significance was identified for only exceptional cases. Only in the case of European artificial intelligence startups, partly funded by debt, was this a significant revenue factor. Again, it was not significant for funding. Previously, in this section of the thesis, it was indicated that patent commercialization is not automatic, and Halle et al. (2014) indicated challenges around it. We must thus reject the hypothesis.

Impact of trademarks on follow-on funding of an artificial intelligence startup by a venture capitalist.

The thesis has identified trademarks as a potentially significant factor (Block et al., 2015). To test this, the following hypothesis was tested.

H_{10c} – Venture capitalists consider trademarks to be a significant factor influencing the funding level.

The results of the generalized linear model suggest that the factor is significant for Europe and the US but not significant for Asia. We still fail to reject the hypothesis. This is because trademarks in Asia behave differently. In Asia, there is no common intellectual property law across the different countries, and the exhaustion doctrine is applied differently.

Cross product factors

In the generalized linear model in this thesis, cross product factors were introduced for two reasons.

1. To study whether patents interact with any other factor for a significant impact on funding.

2. More than a fourth of the US artificial intelligence startups (27%) had acquired another startup, and so had 17% of the European artificial intelligence startups. There was no previous theory around a startup acquiring a startup. The cross product between M&A and other factors were introduced to understand this phenomenon better. No hypothesis was introduced due to a lack of previous theoretical literature.

The generalized linear model finding indicates that acquisition is largely a signaling tool. The cross product between M&A and Late Stage leads to a negative coefficient, and acquiring a patent also leads to a negative coefficient for Asian artificial intelligence startups.

Interestingly, the cross-product factor between M&A and articles indicates slight collinearity with variance inflation factors greater than five but less than 10 for the Asian and European artificial intelligence startups. Collinearity is when the two factors are not fully independent.

On patents, tests were run across both funding and revenue generation. The cross-product factors are not significant for funding (except in the case of Asia, where M&A's, when used to acquire patents, have a negative coefficient) but are significant regarding revenue generation. Patent and article cross product factor are significant in the context of both Asian and European artificial intelligence startups.

Summary of analysis of the follow-on funding.

Before proceeding to the next test, we summarize the findings of follow-on funding and its implications for the gaps identified earlier. The summary is in table 45 below.

Figure 45 – Summary of finding – follow on funding.

Follow-on Funding test			
Hyp.	**Details**	**Gap to be tested**	**Summary of findings**
H_1	For similar industry segments, the number of employees will be a significant factor in the follow-on funding.	The focus has been on qualification of employees but never on the fact that an ability to attract employees is a positive validation of the startup and should provide confidence to the venture capitalist that the startup can scale.	**We failed to reject the hypothesis** - Not only was the this an important funding factor, but also an important component of the prediction model. - Relative size of the startup within a standard industry is important to indicate operational scalability readiness. - Scalability is an important factor for operational profits in the growth / expansion stage that a venture capital invests in
H_4	The number of software applications developed by a startup will be positive correlated with VC funding raised.	In a standard industry segment such as artificial intelligence, it is not enough to invest in technology but to create differentiation. Differentiation will be tested as a part of the patents testing.	**The hypothesis was rejected and is in line with the findings of Baron et. al. (2018)**
H_{8a}	For venture capital funded startups seeking further funding, the number of press articles help provide positive validation for funding.	The theory mainly supports signals as cues for funding. The thesis explores signals as tools for improving venture capital returns.	**We failed to reject the hypothesis for Asia & Europe but rejected it for the US** - US media extends beyond press articles to include signals. - For a smaller test where sentiment analysis was included, the results showed a correlation. The sample size was not large enough to report. - In longitudinal validation of model results, signals normally translated into traction which meant operational progress. This test was restricted to Asia and European startups.

Follow-on Funding test			
Hyp.	**Details**	**Gap to be tested**	**Summary of findings**
H_{9b}	Where the startups have been funded once, patents would be important factors influencing funding efficiency	Patents as signals for commercial opportunity	**We failed to reject the hypothesis for Asia & Europe but rejected it for the US** - For Asia and Europe, the startups were in early-stage whereas in the US, they were in the later-stages. Theoretically, patents, as signals, are more important in the early stages. - Patents were seen as relevant in the longitudinal and model analysis
H_{9d}	There are regional differences in the importance and impact of patents as funding factors.	Correlation between patents and venture capital returns (not startup seeking funding).	**We failed to reject this hypothesis**
H_{10b}	The combination of patents and trademarks should influence a venture capitals funding decision.	Is the combination of trademarks and patents significant for commercialization and hence returns to the venture capitalist	**The hypothesis was rejected** and only found significant for European AI startups partly funded by debt. There too it was significant as a revenue driver
H_{10c}	Venture capitalists would consider trademark as a significant factor influencing the funding level.	Does trademark provide greater comfort to a venture capital of possible returns	**We failed to reject this hypothesis**

First funding/pre-seed funding.

In the US alone, 3.2 million startups are incorporated annually, of which less than 1% are funded (Klaus & Rico, 2023). Most startups spend an average of $70k as establishment costs and are tiny businesses that may scale. However, they are not technically the technology startups that are the focus of this thesis. This number has only been mentioned to detail the nature of the challenge. A pre-seed funding investor/angel investor needs to identify the top firms within these 3.2 million firms. As mentioned previously, this funding stage is important for the entire startup ecosystem and is being considered in this thesis. Also, at the moment, all the funding information consolidators are indicating a slowdown (CrunchBase, 2023)

As mentioned earlier in the thesis, venture capital funding is drying down, and it may be necessary for entrepreneurs to understand what could drive a successful closure through an early-stage facilitator. In addition to that, we want to understand whether the hypothesis defined through the theoretical background can still be relevant at present.

The hypothesis to be tested.

The data test was conducted in partnership with an early-stage facilitator.

1. Pre-seed first funding data for 50 startups.
2. Of the 50 startup funding requests, the early-stage facilitator would choose 4-5 to recommend to its angel investors as potential startups to consider for funding.
3. The selection should be relevant for the angel investors.

The criteria required by angel investors and the data availability against that were mentioned earlier in this thesis in Table 35. Given that full data elements were not available, a few factors were identified during the literature review and will be tested. The details of these are in Table 46.

Table 46 – Details of the hypothesis to be tested.

Data Element	Hypothesis	Descriptive data
Patents	H_{9a}	10%
Trademarks	H_{10a}	12%
Average Market Size (TAM - US$ B)	H_2	$ 24.20
Press articles	H_7	0.90

We ran a simple t test to test these hypotheses and the current factors.

1. A data-centered approach was developed and deployed based on the data extracted. The intent was to select the top ten startups the partner could consider sponsoring to their angel investor network.
2. Simultaneously, the partner set up an investment council to evaluate and gauge the startups independently.
3. Incidentally, the data approach and investment council made the same decision independently. The data-based approach had identified ten startups, whereas the independent investment council narrowed it to 5. The five selected were also among the ten identified through the data-based approach.
4. On data-based algorithms, the data received from the partner was ameliorated with public data and tested for factor significance. The significant factors that align with the literature research are in Table 47:

Table 47: T-test results

	t-test
Patents	**0.751**
Average customer live	**0.012**
Average Market Size (TAM - US$ B)	**1.000**
Press articles	**0.351**

Data indicates that currently, market and customer live (a proxy for trademark) is the minimum requirement for funding. Below are the implications for the hypotheses to be tested. The hypotheses are:

H_2 – For first funding, the market size will be a significant decision factor.

H_7 – For angel investors, signals provide positive validation and help with the funding.

H_{9a} – For early-stage startups, patents will influence the fundability of a startup.

H_{10a} – If a pre-seed startup has registered a trademark or has live clients, it is more likely to receive funding.

First, we consider the market size and hypothesis.

H_2 – For first funding, the market size will be a significant decision factor.

While the work of Maxwell et.al. (2012) has stated that market size is a key factor for an angel investor to decide to fund the first stage. Market size is usually associated with scalability and ability to pivot as mentioned earlier in the thesis. As discussed earlier, both these would require venture capital funding later in the stage when the prototype has been finalized in the current scenario, it seems to be more of a hygiene factor rather than a factor driving funding. A minimum is required, but a large total addressable market will not help funding unless other fundamental are in place.

A close look at the data and its qualitative study indicates that the startups with a high Total Addressable Market were focusing on a business case that reduced their obtainable market size. As a result, they were not considered. Plus, in two cases, there was negative press. Based on this and the test results, it is fair to state that the data is not representative enough to accept or reject the null hypothesis.

The same holds in the case of patents and the hypothesis.

H_{9a} – For early-stage startups, patents will influence the fundability of a startup.

There are only four startups in the sample that have patents. The number is not significant enough to draw a conclusion. For both these hypotheses we can't reject or fail to reject the hypotheses.

From a practitioner's perspective, there is a merit in these findings. Recently, in discussions with early-stage investors, the message has been around.

1. Venture capitalists are no longer keen on scalability alone but want to invest in startups that have positive revenue or profits traction. The same has been covered by startup news sites such as Crunchbase (2022,2023), and Dealroom (2023).
2. Bloomberg (Randles & Pollard, 2023) recently published an article on the Special Purpose Acquisition Companies (SPAC) losing US$ 46 billion investors' money due to bets on non-profitable businesses.

The next few hypotheses should be important as they focus on commercialization or traction. If the market is right, based on what the practitioners are mentioning, those factors should be significant. Focusing on signals that would include the following hypotheses.

H_7 – For angel investors, signals provide positive validation and help with the funding.

And

H_{10a} – If a pre-seed startup has registered a trademark or has live clients, it is more likely to receive funding.

Data has indicated that customer live is strongly associated with a funding recommendation. Customer live implies both a marketing engine and signaling acceptance from the market. One of the biggest risks that practitioners are aware of is whether the product or service will be accepted in the market. A customer's live, signals that acceptance.

Hence, for both, we fail to reject the hypothesis.

For an entrepreneur, these findings imply that traction is significantly correlated with the first funding. In a down market, angel investors look for stronger cues to fund a startup and those cues should largely be in the form of traction and events. Those are two strong signals that could help fundraise.

Unfortunately, one thing that could not be verified is the impact of high degrees on first funding and whether a doctorate helps. This was checked in the subsequent survivability model but not for first funding case in today's context. That could also be an area for further research. Historically, as mentioned earlier in the thesis, academic background helps with the fundraise, but the study was conducted when the funding market was indicating a double-digit growth,

Summary of analysis of the follow-on funding

Before proceeding to the next test, we summarize the analysis of this section in Table 48 below.

Table 48 – Summary of finding – first funding.

First funding test			
Hyp.	**Details**	**Gap to be tested**	**Summary of findings**
H_2	The market size will be a significant decision factor for first funding	The relationship between market size and angel investors has been derived based on interviews and not through a data driven approach. Also, the approach has to be tested for the current negative sentiment market.	**We failed to reject or nor reject this hypothesis** The data and investment council test did not show a significance, but on the other hand, there were extenuating factors that prevented a full test. From a practical standpoint, the current market view is that this factor by itself is not significant and needs to be an interactive factor with cross product of market size and customer traction as a strong funding signal
H_7	For angel investors, signals provide positive validation and help with the funding	Link between signals and first funding	**We failed to reject this hypothesis** Customer interest is considered a strong signal to invest
H_{9a}	For early-stage startups, patents will influence the fundability of a startup.	Patents as signals for potential commercial activity and hence fund 'ability' of the startup	**We failed to reject or nor reject this hypothesis** The data and investment council test did not show a significance, but on the other hand, only startups requesting for funding had filed for patents From a practical standpoint, the current market view is that this factor by itself is not significant and needs to be an interactive factor with cross product of patents and customer traction as a strong funding signal
H_{10a}	If a pre-seed startup has registered a trademark or has live clients, it is more likely to receive funding	Does trademark provide greater comfort to a first stage funding	**We failed to reject this hypothesis** Customer interest is considered a strong signal to invest

Survivability of a funded startup. What factors help the venture capital ensure the safety of its return with a positive exit?

Survival of a funded startup is key to ensuring that the investing venture capital fund receives a return. Whether we reference figure 1 mentioned earlier in this thesis that suggests that 65% of the funded ventures will return less than 1X investment, or the recent 2-6-2 rule (20% bankrupt, 60% less than 1X some near total losses, and 20% high returns) proposed by many industry experts (Hodge, 2023), the venture capital expect some of the investments to go bankrupt.

This section is an attempt to try and prevent some of these bankruptcies. The survival prediction approach and the fundability readiness prediction are what this thesis hopes would help introduce a data-driven approach to venture capital financing. The thesis is not building a model but rather indicating the functions that could be important for the data model building.

The work in this section is based on actual work completed for a venture capital fund struggling with losses. The fund was unable to sustain the losses and had to fold. This survivability model was finalized a couple of years ago, and the results were longitudinally verified half a year ago. Diving straight into the subject, the focus would be on some of the important factors.

Logit regression model to help identify critical functions for survivability.

As indicated earlier, the top data of 1,000 sustainability startups, both closed and active, were selected. Of the sample collected, a total of 196 sustainability startups were drawn at random, of which 91 were active, and 105 were closed startups. The data was selected in a way that ensured that both active and closed startup numbers were balanced and almost similar in the test sample. Let’s start with the data previously mapped in Table 26 and link them with the hypotheses to be verified. The results are in Table 49.

Table 49: Survivability predictions and results.

Data Element	Specific test	Definition	p>|z|, Result - Logistic model	Coefficient	VIF
Risk	Ecosystem: Investment Cross product factor	Does the sustainability startup require a new ecosystem to be built like battery charging If yes, are investments being made for that	0.011	8.39	2.67
Market size and growth	growth dividend	The market grows (GDP) at a certain rate. If the rate is higher than GDP growth, it should lead to new markets for startups to capture	0.025	20.47	**10.47**
Founders profile	Founder with a PhD Cross product factor	In a technology space, a Ph.D. should be an added qualification indicating an ability to create new IP	0.034	11.55	5.49
Signals	Press articles in the last 6 months	Recency of coverage should be more important than previous coverage	0.001	37.13	2.06
Patents	**Not Significant**				
Trademark	Trademarks	Binary variable. Yes or no	0.029	9.21	3.21

Some of the key accuracy rates of the model that can be constructed are below.

```
from sklearn.metrics import  recall_score, precision_score, f1_score, roc_auc_score,accuracy_score
print("Recall:",recall_score(Y,Y_hat))
print()
print("Precision:",precision_score(Y,Y_hat))
print()
print("F1 Score:",f1_score(Y,Y_hat))
print()
print("Roc Auc Score:",roc_auc_score(Y,Y_hat))
```

```
Recall: 0.8791208791208791

Precision: 0.8602150537634409

F1 Score: 0.8695652173913043

Roc Auc Score: 0.8776556776556776
```

The scores can be explained as follows.

- Recall – How good is the model in predicting positive outcomes?
- Precision – The proportion of correctly predicted positive instances among the instances that have been marked as positive.
- F1 score – a score of the model's accuracy
- Roc_Auc_Score – An aggregated metric that specifies the accuracy of the model in classifying positive and negative instances.

All these metrics are close to 87%.

Based on the factors, the prediction was as follows.

	Live	Closed
Live	80	11
Closed	13	92

The data was validated after a year, and only 2 of the predicted live startups had closed. Of the 11 live but predicted to be closed, 3 had indicated negative news.

Analysis of some of the critical factors that can help develop a survivability model.

Six factors will be discussed in this section from the practical and academic perspective. These are risk, market size and growth, founders' profile, patents, signals, and trademarks. The impact of patents will be studied separately.

Risk

The following hypothesis is being tested.

H_{76} – As risk increases, so does the probability of a startup failure.

For H_{6}, the risk involved in a startup would be categorized into ecosystem changes and non-ecosystem changes. An ecosystem change is similar to electrical battery charging networks for electronic cars. Risk in this context would be the cross product of ecosystem change and willingness to invest. For each of the startup considered in this segment, qualitative research was conducted to arrive at this risk category.

In the study, it was identified that.

1. If the need for investment increases, the risk of startup failure increases.
2. The risk is mitigated to some extent if there is an investment from the government to support the ecosystem's development.
3. Without investment, the startup increases significantly. The coefficient is significant and negative in this case.

A recent paper by D'Almeida et al. (2023) validates the findings by suggesting that an entrepreneur's risk increases in an emerging ecosystem; sustainability business models can still be considered as emerging businesses. S&P Global (2021) also mentioned, in the case of DeFi, that an emerging ecosystem represents its own risk.

In the context of the findings and the data analysis, it is fair to state that the null hypothesis must be rejected and the alternate hypothesis to be accepted. The risk to survivability is increasing with the non-mitigated ecosystem risk.

This has significant implications for the venture capital industry, as new technologies continue to evolve, venture capitalist rush to fund them without considering the ecosystem risk. A recent example if of Generative AI. Venture capitalists have funded Generative AI deals, but the ecosystem is not ready. No large corporation is willing to share its data, and the market is moving towards a model as a service with either Open AI, Bedrock, or Bard as a foundation model, with a proprietary small language model for decision making.

<u>Market size and growth</u>

The following hypothesis is being tested.

H_3 – Greater market size will be a key feature for startups in business areas where the business model is under development.

In the data, a partial linkage has been identified with significant multicollinearity. It must be stated here that the sustainability startups selected had an average market size of $12.5 billion in total addressable market, whereas the survivors had a higher total addressable market size of $16.5 billion. A weak correlation was established, but the logit regression results did not indicate significance.

Market size and growth were considered in this study for two reasons.

1. The fact that market size may not be significant was validated by Gompers et al. (2016) in a study of 689 venture capital, who found that none of the business-related factors—business model, technology, market size, and industry—was rated most important by more than 10% of the venture capitals for success or failure.
2. On the other hand, all accelerators and angel investors, the example of Antler given in the thesis earlier and the angel investor investment criteria specified, prefer a large

market size that is growing rapidly due to increased risk from a new, not funded investment. The question being considered was whether a new business model would behave like the risk of a new, unfunded investment.

3. From Gompers et. al.'s (2016) perspective, test was whether market size or the growth dividend can help address the idiosyncratic risk.

That seems to be the case. Sustainability startups usually attempt to reinvent an existing market with new business models focusing on renewable and sustainable business processes. From experience, usually, large market-size processes are selected to be transformed into sustainable offerings. Examples would include solar power, recyclable oil, and electric cars. It could be interesting to gauge the impact of market size on a new industry other than sustainability, but that will need to be covered separately in different research.

Based on the findings, the hypothesis would not be rejected.,. For a business model uncertain market like sustainability, market size, and growth are mildly significant.

<u>Founders profile</u>

Founders' profile was considered from the perspective of a new business model being developed that poses an idiosyncratic risk. The risk was inherent in the process, and related experience or education may help to negate some uncertainty. Hence, the test was to determine whether this hypothesis could be accepted.

H_5 – In a new industry, the previous founder's professional experience may be significant in developing a profitable business model.

Various factors were tested for significance with a logit regression model. These included previous entrepreneurial experience, previous experience, related education, and graduation from top universities.

Significance was identified in two of the important factors.

1. Related education with a Ph.D. and previous experience cross product is significant with a p>|z| value of 0.034.
2. Graduation from a top university with a p>|z| value of 0.006.

Both these findings are consistent with the independent validation by Kaiser and Kuhn (2019) for econ papers sponsored by the Deutsche Post Foundation. The independent regression analysis arrived at a similar conclusion.

Based on the findings, the hypothesis would not be rejected.

<u>Signals / published articles.</u>

The hypothesis being tested was as follows.

H_{8b} – Where the business model is not proven, the number of press articles provides positive validation of the strength of the business case and the survivability of the startup.

The nature of the data enabled a richer analysis. While for follow-on funding, press articles related to the traction or events, the closed sustainable startups enabled a closer sentiment analysis of whether there were signals that indicated that the startup may be in trouble.

This hypothesis had to be rejected, and the reasons for this were as follows.

1. The number of press articles is insignificant. The only significance that can be driven considers the recency of articles and the related sentiment. That would fail as a prediction model as it may be too late to prevent further investment.

2. In sustainability, the sentiment is a dual sentiment of the market and of a new startup. Given the focus on ESG and sustainability, many new startups are highlighted more because they are creating a sustainable solution rather than the strength of the startup. Press articles may not provide accurate signals.

Zero Mass Water and Better Place are two examples of the second point. In Zero Mass Water, the founder team wanted to extract water from the atmosphere, and the solution found much support in the Middle East, with the then-US President approving a significant grant. Better Place developed a swappable electrical car battery where the driver could drive into specific garages and swap a nearly discharged battery with a fully charged one. Both the startups had significant press coverage, but the coverage was more for the problem they were solving rather than the strength of the startup. Both failed.

Trademark

The hypothesis being tested was as follows.

H_{10d} – The presence of trademarks would increase the chances of a startup's survivability.

The hypothesis has been found to be significant and could not be rejected, the p>|z| value for the test was 0.029.

Both patents and trademarks protect the IP of the startups, though they look at different aspects of trade secrets (Vries et al., 2021; Block et al., 2015). Patents refer to the technological aspects of the startup's business model, whereas trademarks refer to the marketing aspects of the startup's business model (Vries et al., 2021). The marketing aspects would be extremely critical for any startup but would be paramount for a sustainability startup.

Sustainability has a new business model, and as mentioned earlier in the thesis, the focus of many scholars is on co-invention. A trademark or an existing marketing chain would then specify that the co-invention has been successful, and the startup is able to generate revenues. Usually, that negates much of the failure risk.

Next, we consider patents and exit. Patents were not considered while studying survivability. This was for the following reasons.

Patents are central to this thesis and its central paradigm. Innovation is a driver for economic growth, with venture capital supporting the growth by facilitating investment in high-technology startups. Patents are a sign of innovation. It becomes critical to understand whether a venture capitalist should consider patents as significant. For patents to be significant for a venture capitalist, they must help with an exit.

Importance of patents as drivers for exit and venture capital returns.

The sample of 151 artificial intelligence startups chosen for the follow-on test included almost half that had been granted patents and half that did not receive patents. The 2021 data was updated to 2023 to understand whether patents helped with an exit. The last few years, as indicated earlier in the thesis, have been challenging from the perspective of funding and exit. If startups with patents are demonstrating a significantly different number of exits, then we can conclude that patents help in exit. Consider the data in Table 50 in the next page.

Table 50: Importance of patents for an exit.

	Revenue growth 2021-23	#of employees	Significant events	Acquired	IPO	Exit
Non-Patents						
Mean	41.81	281.86	0.35	0.15	0.03	0.16
SD	32.16	204.15	0.48	0.36	0.16	0.37
Number	75	75	75	75	75	75
Patents						
Mean	50.09	316.85	0.54	0.10	0.15	0.24
SD	42.07	251.98	0.50	0.30	0.36	0.43
Number	76	76	76	76	76	76
t test	**0.165**	**0.337**	**0.020**	**0.327**	**0.005**	**0.254**

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The T-test value is significant, and hence the hypothesis,

H_{9c} – Patents would impact the exit and hence are valuable for venture capital.

The t-test results of significance of patents of IPO exit are very important to the main paradigm of this thesis. As noted earlier, venture capital returns are tied to an exit, and the t-test results are evidence that the presence of a patent for an artificial intelligence startup, could be helping venture capital significantly with the exit.

Summary of analysis of the survivability and exit

The summary of survivability and exit is Table 51 below.

Table 51: Summary of analysis of survivability / exit

Survivability / Exit test			
Hyp.	**Details**	**Gap to be tested**	**Summary of findings**
H_3	Greater market size will be a key feature for startups in business areas where the business model is under development.	Does market size help a venture capitalist estimate idiosyncratic risk for a new segment?	**We failed to reject this hypothesis** A mild significance was identified between the growth dividend (industry growth - GDP growth) and survivability. While the p value was significant, the VIF was high and denoted multicollinearity
H_5	In a new industry, previous founder professional experience may be significant to develop a profitable business model.	When business model is not tested, previous experience and industry knowledge of the founder could play a significant role	**We failed to reject this hypothesis** Significant P value was denoted for a founder with a PhD and founders from top universities with the right experience
H_6	As risk increases so does the probability of a startup failure.	Technology introduction may create ecosystem risks, and it is important that these risks be addressed to protect venture capital investments.	**We failed to reject this hypothesis** Significant P value was denoted for cases where there was an ecosystem risk created by a business model but was being addressed through investments
H_{8b}	Where the business model is not proven, the number of press articles provide positive validation of the strength of the business case, and survivability of the startup.	Number of press articles as a signaling stability factor to the market	**We reject this hypothesis** Significant p value was detected in correlation with recent articles but that will not help protect the investment
H_{9c}	Patents would impact the exit and hence is valuable for a venture capital.	Impact of patents on survivability and exit of the startup.	**We reject this hypothesis** Significance was not detected
H_{10d}	The presence of trademarks would increase the chances of a startup's survivability.	Trademarks as signals for commercial opportunity	**We failed to reject this hypothesis** Significant P value was denoted. Trademarks help with commercial activity, and by default with survivability

Implications, contributions, and areas of further research

The study is one of the few studies considering the link between venture capital funding and economic growth. Also, this is one of the few studies that focuses on improving returns for the venture capitalist rather to provide cues to the entrepreneur on ways to fund raise.

Using this paradigm as the basis, it has evaluated the entire startup ecosystem across first funding through angel investors and accelerators, venture capital funding, and protection of venture capital returns by a deep dive into factors assisting with survivability and IPO exit. The thesis also considers regional differences for follow-up on funding across the US, Europe, and Asia and draws the significance of patents as not just knowledge indicators but also as key drivers funding and exit drivers. Such extensive coverage and a total view of the entire funding cycle have not been identified in any other work.

The work has multiple benefits. One of the benefits is that, for a venture capitalist, it seeds the idea of moving away from heuristics to a data-driven approach. Secondly, it can indicate important features that the venture capitalist could consider improving funding efficiency. The funding efficiency and features are not just validated through quantitative models but also supported with longitudinal research and case studies. Thirdly, while other studies have mainly considered direct factors, this thesis has also considered second-level factor cross products to bring a better understanding of the features. Finally, with this study, readers can better appreciate the venture capital world as they can understand its relationship with economic growth. The patent deep dive also helps to bring greater appreciation to innovation and the need to build patents.

The thesis also leaves some gaps that can be explored in future research. These include.

1. As a part of the analysis of follow-on artificial intelligence startup funding, it was found that patents tended to be more important in the early stages as compared to the late stages of funding. That could be an area of future study.
2. Technology investments have been stated to be an important feature of follow-on funding. Yet, when we studied only the high technology segment of artificial intelligence, it was not identified as a significant feature. Yet, it is an important factor in practice. Creating the right model for technology investments in a high-technology world that would help startups differentiate from others is an area of future research.
3. Sustainability startups usually attempt to reinvent an existing market with new business models focusing on renewable and sustainable business processes. From experience, usually large market-size processes are selected to be transformed into sustainable offerings. Examples would include solar power, recyclable oil, and electric cars. It could be interesting to gauge the impact of market size on a new industry other than sustainability, but that will need to be covered separately in different research.

Conclusion

Wrapping up this document is a summary of main conclusions from this thesis in line with the research questions raised.

These are enclosed in Table 52 below.

Table 52: Conclusion

Category	**Area of focus**	**Stage if applicable**	**Summary of main findings**
Research questions	Can machine learning algorithms help define which startups to fund? If yes, what are the factors that an investor and investee need to be aware of.	Follow on funding	**Yes, the factors can be identified through algorithms and models tested based on the factors. In the study, the following factors were identified as significant** **Follow on funding: critical factors** -Late stage -Number of employees -Signals -Patents -Trademarks <u>Cross products</u> - Acquisitions in late stage

Category	Area of focus	Stage if applicable	Summary of main findings
Research questions	Can machine learning algorithms help define which startups to fund? If yes, what are the factors that an investor and investee need to be aware of.	First funding	**First funding: critical factors** - Customer live (trademarks and signals) - Market size (as cross product) - Patents (unable to reject or fail to reject)
		Survivability / Exit	**Survivability / exit: critical factors** - Patents (for IPO exit only) - Trademark Cross products - Investments to address ecosystem risks - Founder from top university or a PhD - Signals in last 6 months - Growth more than GDP growth rate

Category	Area of focus	Stage if applicable	Summary of main findings
Research questions	The VC investment process is equivalent to option financing with stage-wise financing. Is there a way to predict which startups are ready for the next round of funding?	Follow on funding	Yes, the models can be defined based on Generalized Linear models and critical factors. The following results were noted for the models defined for this exercise. **Model validation - Longitudinal accuracy of prediction - fund / do not fund** - Recommended to fund - Accuracy (82%) - Recommended to not fund - Accuracy (76%) **Opportunities to rationalize found** - Funding has a higher variance than revenues - 5-10% of the funding amount could have been deployed more efficiently (US$ 25 billion opportunity)

Category	Area of focus	Stage if applicable	Summary of main findings
Research questions	The thesis has also discussed that VC investments are illiquid till exit, and exit may be a 5–7-year timeframe. The VC's investment is lost if a startup can survive that duration. Can machine learning help to predict the survivability of a startup?	Survivability / Exit	Yes, the study develops logit regression models based on critical factors with the following results **<u>Model results</u>** - Recall @ 87% - Precision @ 86% - F1 @ 87% - Roc_Auc @ 88% Model predicted - 80 out of 91 live startups correctly - 92 out of the 105 closed startups correctly **<u>Longitudinal results</u>** - Only 2 out of the predicted 80 live had closed after a year. - Of the 11 live but predicted to be closed by the model, 3 were showing early struggles with survivability

Category	Area of focus		Summary of main findings
Research questions	Startups are considered important as they help in the innovation ecosystem's growth. Patents are often considered a leading indicator of innovation. Are they important in the context of knowledge-based startups? Also, it is important to consider the relative importance of other factors.	Survivability / Exit	t-tests of the two equivalent samples of - AI startups with patents - AI startups that did not have a patent granted to them Indicated a significant correlation between startups with patents and IPO. The correlation was also found in significant events, Patents, in the sample, help with IPO.
	Do the factors that determine which startups to fund vary across the regions? The three regions considered in this study are the US, Europe, and Asia with a deep dive into artificial intelligence startups funding,	Follow on funding	Yes, - Asia and Europe samples have similar characteristics and similar Generalized Linear Model results. - US AI startups were behaving differently in the samples chosen

Previous publication at the 4th Sophia AI Summit, 2021:

Role of Patents and Trademarks in funding and revenue generation of AI startups: a cross-market study in EU, Asia, and the US

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The purpose of this research is to understand whether patents and trademarks are significant drivers of funding for artificial intelligence (AI) startups by venture capital firms (VC) and whether those help in driving revenue generation for these startups. Data of 573 startups across Europe, the US, and Asia were taken from Crunchbase and fitted using a Generalized Linear Model (GLM) to understand the significance of patents & trademarks. The results indicate that while both variables play a significant role, especially in Europe, AI startups prefer trademarks in the early stage.

Specific to Europe, an illustration of this is that while the Venture Capital (VC) value patents higher, only 25% have filed for patents, whereas 76% have registered trademarks. This phenomenon of preference for trademarks may have a broader implication on the future growth of these startups and the economy's overall growth.

EU (2019) briefings referred to AI as an engine of growth in Europe, expecting it to double the growth rate by 2035. European Investment Bank (EIB,2021) extended the discussion on the importance of AI e by including the importance of Venture Capital (VC) infrastructure, implying the importance of AI startups. Previous research had indicated that startups are essential for growth as they play a critical role in introducing radical technology that leads to economic growth (Colombelli & Quatraro, 2019; Fukugwawa, 2018).

Previous research has indicated that patents and trademarks are significant drivers of funding and help drive revenues. Zhou et al. (2014) viewed patents and trademarks as technological and marketing signals that should positively impact an AI firm's growth and funding. Important to note that the treatment of patents and trademarks varies across Asia, Europe, and the US. In Asia, trademarks have to be registered locally in each country. Asian laws protect unregistered trademarks if they have gained goodwill (European Commission, 2020). Research of patents in the US indicates that an absence of a previous artifact can lead to a patent grant (NBER, 2002).

Total 573 startups across Europe, the US, and Asia were analyzed to understand the drivers for revenues and funding. Of the 573 startups, 258 were Europe based, 179 were US based, and 136 were Asia based. Among the 258 European startups, 120 were funded only through VC, while 138 AI startups were funded through a mix of debt and VC funding. GLM was used for analysis as the data failed the normality test. The model included both patents and trademarks as drivers of both funding and revenue and their cross product with late stages of funding and other variables such as signals and M&A. Both patents and trademarks were considered dummy variables in the models.

The results show that patents and trademarks are essential drivers for funding European AI startups primarily funded by VC. Patents are valued more by 30% as compared to trademarks by the VC partners. For AI startups partly funded by debt, patents are not a significant contributor to the overall funding. Thus, EIB's (2021) focus on VC is validated. Only trademarks are significant as drivers for revenue. Patents granted in the later funding stage (captured as a cross product variable) results in revenue reduction.

For Asian AI startups, patents and trademarks are significant drivers of funding, with patents having a 40% higher coefficient than a trademark for VC funding. Patents also drive revenues, but the cross product between late-stage funding and patents has a negative coefficient. For US AI startups, VCs value trademarks and not patents, and only trademarks influence revenues. The NBER (2002) findings could explain the lack of significance of patents in the US.

Patents' lack of impact on revenue has a vital significance for the plan for AI startups, as engines of radical technology, driving growth. While patents are not a significant factor across both funding & revenue in the US, in both Europe and Asia, the cross product between late stages of funding and patents reduces revenue. Further, in Europe, patents are not significant as a driver of revenues. The results may indicate that AI startups are challenged in the commercialization of patents, as indicated in previous research (Halle et al., 2014). Challenge in commercialization may be the reason that in Europe, within the sample of 120 startups, only 25% filed a patent while 76% registered a trademark. EU (2019) may need additional steps to double the economic growth rate with AI startups as drivers of this growth.

Key Words

Artificial Intelligence (AI), Venture Capital (VC), Trademarks, Patents, Governance, Management

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