Working Paper 25-020

Priors, Experiments, Learning and Persuasion in (Bayesian) Entrepreneurial Finance

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Abstract

At the heart of entrepreneurial finance lies a persuasion challenge: regardless of the strength of an entrepreneur's belief in the potential of their idea, they typically need to convince investors to provide the financial capital required for its commercialization. How should entrepreneurs approach this challenge in order to maximize the chance of raising the required external finance? Why does it appear harder to persuade venture capital investors to finance startups in certain industries and regions and in certain periods of time? Are there systematic frictions preventing entrepreneurs from effectively persuading investors in certain settings and if so, what can be done to reduce them? In this chapter, I discuss answers to these and other questions through a conceptual framework in which investors update their beliefs about a startup's prospects through a sequence of investments over time.

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1 Introduction

At the heart of entrepreneurial finance lies a persuasion challenge: regardless of the strength of an entrepreneur's belief in the potential of their idea, they typically need to convince investors of its potential in order to raise the financial capital required for its commercialization. Can entrepreneurs take certain steps to increase the chance of raising the required external finance from investors? Why does it appear harder to convince venture capital investors to fund startup commercialization in certain industries and regions and in certain periods of time? Are there systematic frictions preventing entrepreneurs from effectively persuading investors in certain settings and if so, what can be done to reduce them?

In this chapter, I discuss answers to these and other questions through a conceptual framework in which investors update their beliefs about a startup's prospects through a sequence of investments over time. In Section 2, I first show how this 'learning perspective to multi-stage financing' is closely related to the ideas discussed in Agrawal et al. (2024) chapter on Bayesian Entrepreneurship. Next, In Section 3 I discuss how this learning perspective helps explain patterns of venture capital finance across industries and over time that are hard to understand when considering staged-financing exclusively as a means of governance to mitigate agency problems. In Section 4, I discuss important generalizable and teachable lessons related to the practice of entrepreneurial finance that emerge from this perspective. Finally, in Section 5, I end with some thoughts on the promise of more closely connecting the entrepreneurship literature on 'Bayesian entrepreneurship' outlined by Agrawal et al. (2024) with the economics and finance literatures on learning through experimentation, particularly in the context of entrepreneurial finance.

2 A learning perspective to multi-stage financing

A key contribution of the finance literature on venture capital has been to document the important role that VCs play in supporting the growth of startups through monitoring, governance and value-added support of entrepreneurial teams (Sahlman 1990; Lerner 1995; Hellmann 1998; Hellmann and Puri 2002; Bernstein, Giroud, and Townsend 2016). Among the many tools that VCs bring to bear in this process, scholars have also documented the particular role of multi-stage financing in this governance process, by enabling investors to provide funding for the venture only when management teams continue to meet targets and hence mitigating agency problems between investors and management (Gompers 1995; Cornelli and Yosha 2003; Tian 2011).

A conceptually distinct role of staged financing, however, is to help both entrepreneurs and investors *learn* about the prospects of a venture before committing further resources towards its development (Metrick and Yasuda). Although this idea is perhaps implicit in research considering multi-stage financing from a monitoring and governance perspective, I outline below why it helps to explicitly consider it as a distinct benefit of multi-stage financing.

First, many entrepreneurial ventures, particularly those commercializing entirely new products or technologies, face fundamental uncertainty about the venture's prospects. Which of the many novel cancer treatments currently under development will pass multiple clinical trials and be deemed efficacious enough to become commercially available treatments? Which of the several battery technologies under development will be sufficiently cost-effective to be adopted at scale? Which of the hundreds of consumer-facing software applications being developed will gather sufficient traction with consumers to make them worth financing to scale? Although asymmetric information and agency frictions between investors and entrepreneurs are always relevant, a large share of the uncertainty in these contexts is likely to be symmetric – in that neither the entrepreneur nor the investor knows the answers to those questions.

Second, and perhaps more importantly, entrepreneurs and investors do not just passively receive cost-less signals about the ultimate promise of a venture. More information about the venture's potential can only be generated through an investment into the startup (Bergemann and Hege 2005; Bergemann, Hege, and Peng 2008; Metrick and Yasuda). Entrepreneurs and investors can make decisions about what they want to learn, in what sequence, and with what fidelity.This approach to learning builds on a long literature in economics that considers the optimal approach to acquiring or generating economically valuable information in dynamic settings (Grossman, Kihlstrom, and Mirman 1977; Weitzman 1979; Aghion et al. 1991; Bolton and Harris 1999; Bergemann and Hege 1998, 2005). In this conceptualization, the act of incurring a cost to generate the relevant information is described as conducting an experiment. The experiment generates information that allows decision makers to update their prior beliefs. Learning stems from priors being updated (which is typically assumed to happen using Bayes rule). In turn, learning enables economic agents to make better decisions.

Explicitly focusing on the learning perspective to staged-financing is therefore valuable because in this framing, one of the important ways in which value added investors such as VCs can help entrepreneurs is by designing more effective experiments – that allow for better decision-making around the future path of the venture completely independent of agency considerations. It also allows for an understanding of how costs and constraints to the ability to learn and/or persuade investors can have consequential effects on the rate and direction of venture capital in a manner that is distinct from factors related to monitoring and governance.

This learning perspective to multi-stage financing is closely related to the ideas discussed in Agrawal et al. (2024) chapter on Bayesian Entrepreneurship. Indeed, they share an intellectual lineage in that they both build on fundamental insights emerging from information and decision theory and can both be seen as trying to understand how to improve entrepreneurial decision making in the context of uncertainty.

2.1 A framework for learning through multi-stage financing

To guide the discussion in the next two sections, I outline a simple framework for multi-stage financing that is focused on learning through experimentation. To focus on the insights emerging from this learning perspective, the framework abstracts away from potential agency frictions between entrepreneurs and investor and focuses attention on the investor's beliefs. Specifically, I consider a startup that requires $\$K$ to commercialize its technology that may or may not work. The investor believes that it will be successful with probability p_0 and if so worth V while with probability $1-p_0$ it will be worth nothing. Abstracting away from the discount rate for simplicity, the expected value of the project is $p_0V - K$ and the venture will only be financed if $p_0V > K$.

Alternatively, the investor can finance an experiment at cost C before committing the full amount K. The result of the experiment could involve achieving some milestone such as showing initial customer traction or initial proof of technological success in the lab. The likelihood that the experiment generates positive intermediate information and passes the milestone is p_M, while the likelihood of generating negative information and failing to achieve the milestone is $(1-p_M)$. On passing the milestone, the investor updates their belief about the chance of ultimate success to p_P, while their posterior probability of the chance of success if the experiment fails is p_F. To be equivalent to the scenario when no experiment is run, it is assumed that $p_P * p_M + p_F * (1 - p_M) = p_0$, i.e., the unconditional probability of success is the same whether or not the experiment is run. The investor's decision tree is depicted in Figure 1 below:

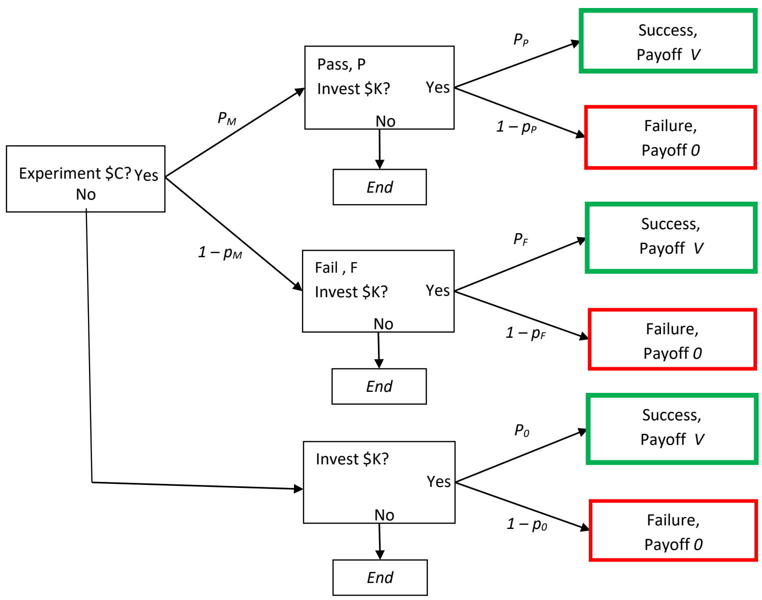


Figure 1: Investor's Decision Tree

Looking at the investor's decision tree highlights two important points. First, financing an experiment is not always the dominant strategy for the investor. The investor will only prefer to finance an experiment in cases where it impacts their decision on whether or not to invest. This cannot hold, for example, for any project that has a positive expected value even after the experiment fails or for a project that has negative expected value even after the experiment succeeds. In these cases, running the experiment is just a waste of resources because the information generated has no impact on the investor's decision to invest or not. However, suppose that $p_0 * V - K < 0$ and that $p_P * V - K > 0$ while $p_F * V - K < 0$. Then the investor's default position without an experiment is not to invest but if the investor financed the experiment, they would want to re-invest if the venture meets the milestone and avoid investing if the venture fails to meet the milestone. The investor would therefore be willing to pay to update their beliefs about the likelihood of ultimate success based on whether or not the venture met the milestone - since the results of the experiment can change their default decision to not invest.[1]

Second, since the value of an experiment stems from its ability to change decisions, the experiment that is most valuable to a decision maker depends on *their specific prior belief* about the venture's prospects. In this sense, the most relevant experiment in a given context is intricately tied to the priors of the decision maker. Later, we discuss how the amount the investor is willing to pay to finance the experiment is also related to the degree they are able to update their beliefs (i.e. how much they learn from the experiment's results). For now, we can see that financing the experiment is most valuable to the investor in situations when relatively small investments can reveal information that impacts their investment decision, and that the ideal experiment itself develops on their priors.

3 Implications for Entrepreneurial finance

In this section, I discuss a number of implications for Entrepreneurial finance that arise from this learning perspective to multi-stage financing, including ones that are not immediately obvious when considering staged-financing as a tool only for monitoring and governance.

3.1 Value inflection is tied to the resolution of uncertainty

The most natural and intuitive implication of the learning perspective to staged financing is that experiments generate information that resolve uncertainty. In the context of the

[1]Similarly even if $p_0 * V - K > 0$, an investor may find it worthwhile to finance an experiment if learning the result enables them to exercise their abandonment option, thereby changing their default decision to invest.

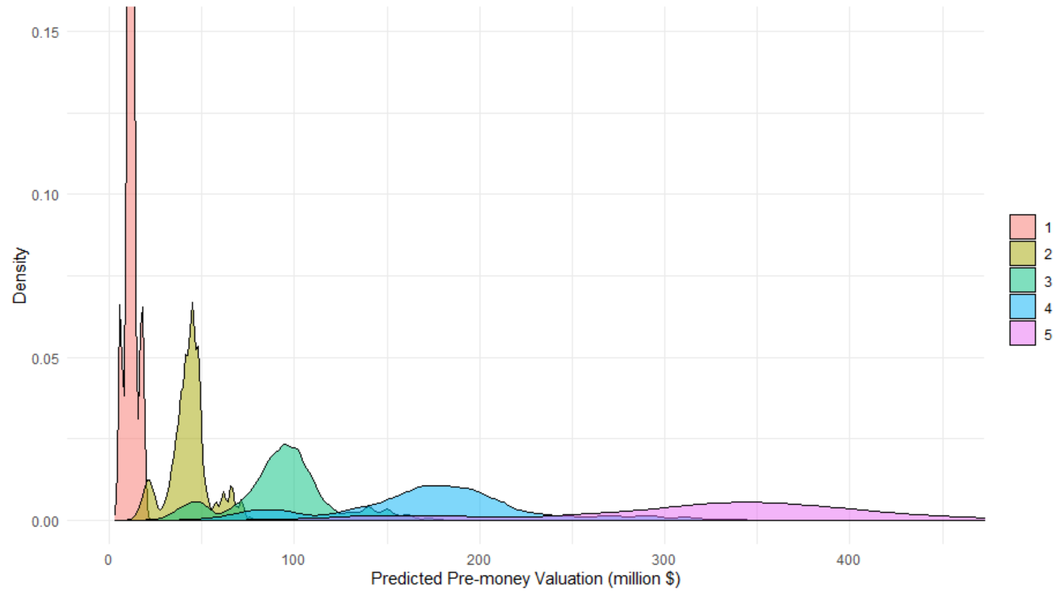
framework above, we can think of $V * (p_P - p_F)$ as the amount of the information revealed by the experiment or the amount that the decision maker can learn from the experiment's results.

On one extreme, an experiment might demonstrate nothing, i.e., $V * p_P = V * p_F$. That is, the probability of earning V is the same no matter the experiment's outcome, so no uncertainty is resolved by the experiment. Alternatively a perfect experiment would imply $p_P = 1$ and $p_F = 0$, meaning that passing or failing the milestone would completely resolve uncertainty about the prospects of the venture.[2] Holding K, p_0, V, and C constant, one can see that the resolution of uncertainty leads to an increase in the posterior probability of success for ventures that pass the milestone. This in turn leads to an increase in expected value, or 'value inflection'.

Figure 2, using data on the pre-money valuation of all US startups between 2013 and 2022, documents the progression of startup valuation across rounds of funding. The pattern is consistent with a view where investors update their beliefs about a startup's potential across multiple rounds of funding, reinvesting only in those whether they update positively and abandoning funding in ventures where they don't.[3] It is worth emphasizing that in this framework, failing to meet a milestone is not a reflection of entrepreneur effort since there is no agency friction in this model. Failure in this model stems simply from the fact that the experiment revealed that the venture is unlikely to work at scale (say because of weak demand, or the inability of the technology to work as initially hypothesized.) This is consistent with the notion that failure can sometimes be good and that in these

[2] Note that the experiment is not more or less important if the project is riskier - a risker project might be one with a larger V and smaller probabilities of success, p_G and p_B - but the information revealed by the experiment, $V * p_G - V * p_B$, could be the same. Thus a project with valuable experiment and the risk of the project are related but not the same.

[3] Note that while consistent with the view of updating beliefs about valuation across rounds, the Figure itself does not provide definitive evidence on this view.



This figure displays density plots of predicted pre-money valuation in levels, taken from the Poisson regressions $\log(\text{Pre-money}) = \beta\text{DealOrder}_i + \gamma\text{FirmAge}_i + \alpha\text{Industry}_i$. FirmAge is defined as the difference in years between the deal year and the year the startup was founded. Density plots of pre-money valuation are deal orders. To improve readability, firms with greater than 450 million pre-money valuation or density more than 0.15 are not included in the plots despite being in the regression.

Figure 2: Evolution of Pre-Money Valuation across rounds of financing

instances 'failing fast' is often lauded as the best course of action.

3.1.1 Designing more informative experiments leads to greater value inflection (if the milestone is achieved)

Having discussed how value inflection is tied to the resolution of uncertainty, I turn to discussing *experiment design* can impact the degree of information generated by experiments. Similar to the discussion in Agrawal et al. (2024) and Bolton et al. (2024), one can characterize an experiment by its ability to correctly predict success and failure. Similar to language used in medical diagnostic tests, let $s_1 = P(s = P|v = V)$, be the probability the venture passes the milestone in the event the venture will actually be successful and will generate V, and $s_2 = P(s = F|v = 0)$ be the probability that the experiment fails to pass the milestone when the venture is a failure. In other words, the parameter s_1

captures the *sensitivity* of the experiment, with $(1 - s_1)$ denoting the *rate of false negative* outcomes if the venture failures to reach the milestone. Similarly, s_2 captures the *specificity* of the experiment, with $(1 - s_2)$ denoting the *rate of false positive* outcomes if the venture passes the milestone.

	Success (Payoff V)	Failure (Payoff 0)
Pass Milestone, $s = P$	$Sensitivity(s_1)$	$FalsePositive(1 - s_2)$
Fail Milestone, $s = F$	$FalseNegative(1 - s_1)$	$Specificity(s_2)$

Given priors that the Technology works are p_0, the probability of passing milestone, $p_M = p_0 s_1 + (1-p_0)(1-s_2)$. The posterior probability of achieving V, $p_S = \frac{p_0 s_1}{p_0 s_1 + (1-p_0)(1-s_2)}$. Holding K, p_0, V, and C constant, and given that $V > K$, it can be seen that the net gain from the experiment is strictly increasing in both s_1 and s_2. This implies that the best experiment design in terms of maximizing value gained from information discovery is the one with the greatest sensitivity (the highest s_1) and the greatest specificity (the highest s_2). Note that a perfect experiment has $s_1 = 1$ and $s_2 = 1$, the greatest specificity and sensitivity possible, and therefore, if feasible, yields the highest gain.

It is also worth nothing that $\frac{dP_M}{ds_2} < 0$ and $\frac{dP_S}{ds_2} > 0$, i.e. designing experiments with a lower likelihood of generating false positives makes it less likely that the venture will achieve the milestone, but *conditional on meeting the milestone* will lead to a higher posterior probability of success. This captures the notion that 'more rigorous experiments are harder to pass but generate more value inflection if achieved'.

Investors value more rigorous experiments – equivalent of having met more aggressive milestones at a given level of development – because it reduces the likelihood of them having to commit further funding to a venture due to a 'false positive'. In turn, they are willing to pay a higher price for the information generated by this experiment. In practical terms, this stems from them requiring a lower share of the equity in the venture to provide the same amount of capital to finance the scale-up. In sectors where there are a large number of equivalent firms, VC investors even provide benchmarks for ventures with firms having met more aggressive benchmarks receiving higher valuations.[4] Indeed, as seen in Figure 2 firms at equivalent points of their development can have very different valuations based on investor beliefs.

3.2 Investor Persuasion

One of the important insights emerging from the framework above, which is also emphasized in Agrawal et al. (2024), is that an optimal experiment does not exist in isolation. Rather, the experiment that generates the most amount of information for a given venture depends on the specific priors of the decision maker involved. This insight is important as it highlights that since an entrepreneur needs to persuade an investor to fund their venture, it is the *investor's priors* that the entrepreneur cares about updating. To the extent that their own beliefs about the prospects of the venture are different from those of the investor, the entrepreneur needs to focus on generating the information that will be most important in shifting investor priors.

This also highlights the importance of understanding investor priors and how they are shaped. Indeed, the specific networks, incentives and prior experiences of individual investors appear to be important in shaping how information is acquired, aggregated and filtered by investors (Bernstein, Korteweg, and Laws 2017; Hu and Ma 2021), which has important implications for what innovations are financed and in turn, on the direction of innovation (Ewens and Townsend 2019; Gompers et al. 2014; Howell and Nanda 2023). Equally important, the ability to frame and interpret experiments may itself be a skill,

[4] This is common practice for Enterprise Software companies. For example, see https://www.scalevp.com/scale-studio/.

particularly in the context of power law information distributions (Malenko et al. 2024). This motivates the need to better-understand how the backgrounds of decision makers and the organizational contexts in which they make decisions can have a systematic impact on which ventures tend of receive financing (Lerner and Nanda 2020).

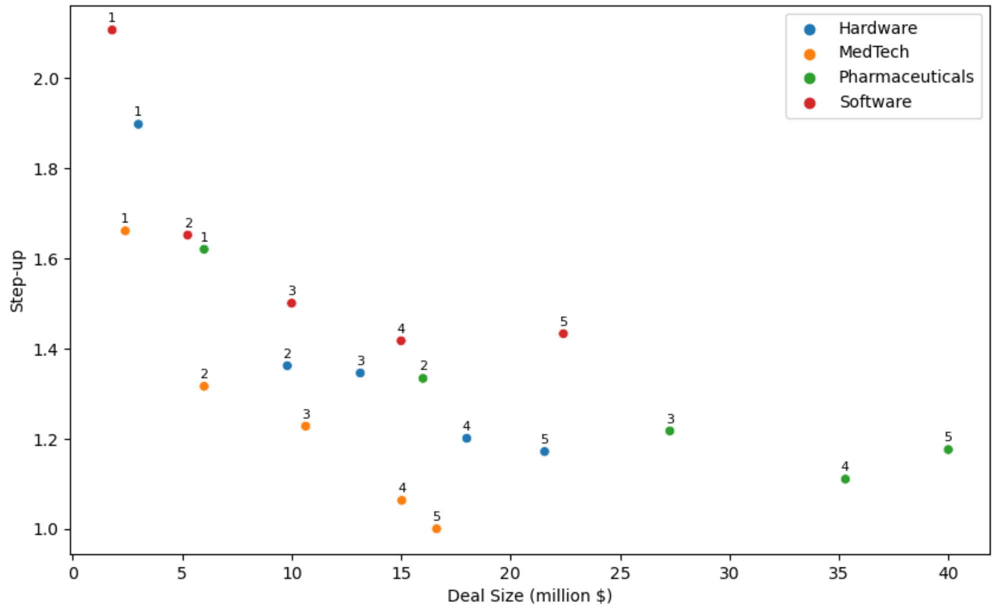
Bolton et al. (2024) also document how there may sometimes be incentives for entrepreneurs to design experiments in ways that make it more likely to pass an intermediate milestone. Conditional on passing the milestone, however, the venture is less likely to be ultimately successful. They show that this moral hazard in experiment design can undermine investor confidence and lead to a market failure in the provision of funding where investors are unable to fully understand the nature of the experiment from which the results were generated. Approaches to validating the experiment design or reducing such moral hazard can play a role in reducing such market failure.

3.3 Costs and constraints to financing experimentation

There is growing evidence that costs and constraints to investors' ability to finance experimentation can also have real effects. In this section, I discuss how such costs and constraints can shape variation in what is financed across industries, regions and over periods of time.

3.3.1 Industry variation in costs and informativeness of early experiments

Recent work discusses the narrow band of innovation that VC investors tend to finance (Lerner and Nanda 2020). While there are many potential non-mutually exclusive explanations for this, I document here how the cost and information value of each round of financing vary across industries, and show how these patterns are consistent with the disproportionate rise in the financing of software-related applications by VC investors in recent years.



This figure shows the relationship between deal size and step-up. Step-up at round t is defined as $\frac{\text{Pre-Money}_{t+1}}{\text{Post-Money}_t}$. Industry groups are color coded. The number on each point represents the round number.

Figure 3: Value inflection and cost by industry

Figure 3 shows the median cost and the median step-up in valuation associated with the first five rounds of financing across different sectors. It can be seen that Software ventures tend to consistently generate higher value inflections across rounds and also require substantially less capital than Hardware and Pharmaceutical sectors. This makes software a much more attractive of a sector to invest in and helps to explain why the over five-fold growth in venture capital backed startups in the past decade have been driven largely by Enterprise Software, Consumer Internet and other sectors building heavily on Software technology.

Ewens, Nanda, and Rhodes-Kropf (2018) trace this dramatic rise to the substantial drop in the cost of early rounds of funding for software ventures, driven by the advent of cloud computing. They show how the projects that were most likely to benefit from this drop in the cost of early experiments were 'long shot bets' – startups with small chances of a large outcome, where an investor can learn a significant amount from an initial experiment.[5] Consistent with the predictions of the model, they find that relative to sectors that did not benefit from the cloud computing shock, industries that benefited from a decline in the cost of starting due to cloud computing experienced a a large increase in the number of startups that were more likely to fail. Conditional on not failing however, these startups experienced larger step-ups in value from the first round to the next. Ewens, Nanda, and Rhodes-Kropf (2018) highlight that by making the real option value of these early experiments greater, the advent of cloud computing led to a shift in the composition of startups that VCs funded towards sectors where the value of learning through the initial experiment had increased.[6] Although technological advances have since also led to falls in the cost of early experiments in other sectors (e.g. gene sequencing and gene editing technologies such as CRISPR for drug development and rapid prototyping/3D printing for Hardware technologies), the lower costs and higher step-ups associated with the typical software investment continue to make them attractive investments for VCs. As can be seen from Figure 4, the total investment into IT Hardware, Biotech and Medtech, and Energy, Materials and Resources has declined substantially over the past 20 years, from about 50% in the early 2000s to about 25% in 2023.

[5]In the context of the framework above, with small probabilities of success (p_0) but where the information and hence value of the abandonment option is high ($V * p_P - V * p_F$ is large).

[6]Ewens, Nanda, and Stanton (2024) also point to the ability of VCs to reduce the burden of nondiversifiable risk (Hall and Woodward 2010) for founders by providing founder-CEOs higher levels of cash compensation once the firm has a product. They show that consistent with theory, sectors in which uncertainty is resolved more slowly and hence have a longer time to product have have a lower likelihood of selection into VC backed entrepreneurship.

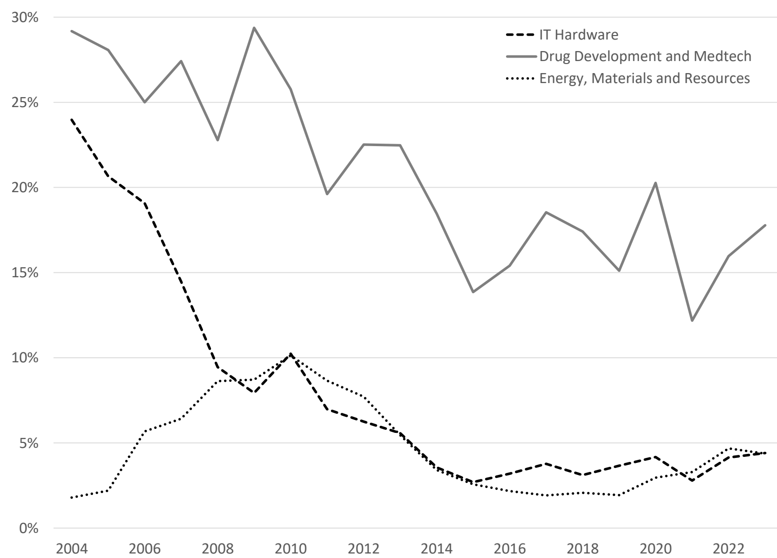


Figure 4: Share of US VC investment across sectors, 2004-2023

3.3.2 Venture capital booms and busts

Venture capital funding for startups is notoriously volatile Gompers et al. (2008); Janeway, Nanda, and Rhodes-Kropf (2021). In fact, even the *risk* of reduced future funding can lead venture capital investors to shift the nature of firms that they back during downturns (Nanda and Rhodes-Kropf 2013, 2017a; Howell et al. 2020).[7].

When seen through the learning perspective of multi-stage financing, this is consistent with early stage investors reacting to what they believe to be shifts in the priors of later stage investors. Specifically, if early stage investors forecast a drop in the willingness of later stage investors to fund startups in a given sector at the next round of financing, it is rational for them to respond to this belief by changing what they choose to finance today (Nanda and Rhodes-Kropf 2017a). A belief that it will be harder to secure a round of financing in the next period also reduces the value of experimentation in the current period (since even if milestones are hit, firms are less likely to get funded), leading to safer,

[7] see also https://articles.sequoiacap.com/rip-good-times

less novel firms being prioritized in terms of funding. Another important implication of this is that a few deep-pocketed investors – who are the ones involved in later stage financing – can have a disproportionate role in shaping what is funded because the much larger number of early stage investors (rationally) focus on trying to predict the priors of these late stage investors and respond accordingly.

3.3.3 Institutional and cultural factors

While many explanations abound for the differences in the rates of high-risk entrepreneurship across regions, one set of arguments has focused on institutional factors such as bankruptcy law (Acharya and Subramanian 2009; Cerqueiro et al. 2017) as well as on cultural factors such as the stigma of failure (Landier 2002). Nanda and Rhodes-Kropf (2017b) highlight how including a cost of early failure for the entrepreneur if intermediate information is negative reduces the value of experimentation for investors, even though they do not directly pay the failure costs. This is because the VC and entrepreneur must negotiate over any surplus generated by the project and stigma from early failure lowers the entrepreneur's expected payoff. If the total expected value of the project does not generate enough to cover the costs borne by both the entrepreneur and investor then the entrepreneur and investor will not be able to find a deal that will induce them to both participate. The deals where they do agree will be ones that will tend to ones with less uncertainty. By committing to be failure tolerant, investors may shift the projects they fund away from ventures where more can be learned through experiments. To the extent that more radical innovations are associated with greater uncertainty, this implies that a commitment to being failure tolerant can change what investors would want to finance. This provides a different perspective on the relationship between failure tolerance and innovation (Manso 2011; Tian and Wang 2012) by showing that failure tolerance impacts both the desire to engage in risky innovation by entrepreneurs and in the willingness to finance such innovation by investors.

4 Insights for Entrepreneurs

The learning perspective on multi-stage financing is also appealing in that it provides clear actionable insights for practitioners, that I have found to resonate considerably with entrepreneurs, investors and other individuals engaging in the financing ecosystem. I discuss a few of these below:

4.1 How much to raise and how to structure financing?

The insight that entrepreneurs need to focus on the priors of those who will provide the next round of financing leads to multiple useful insights. First, it focuses attention on the specific information that will need to generated to convince the next round's investor to engage. Understanding what they need to see to be convinced to invest and what needs to be learnt to help convince them transforms an amorphous fund raising task into something quite concrete.

Second, it allows entrepreneurs to target value-inflection milestones: The milestones that entrepreneurs aim for at each financing stage should have the potential to meaningfully increase the value of the venture if achieved. In other words, each milestone should help resolve a meaningful amount of uncertainty about the venture's viability – in the eyes of the next round's investors – and thus justify a significant "step-up" in valuation from one financing round to the next (e.g. from a Series A to Series B round). By understanding variation in the milestones that are achieved for ventures at a similar stage of progression as the focal venture, it also allows an understanding for the level of 'experiment design rigor' that needs to be targeted to achieve a desired level of value inflection (e.g. how variation the degree of traction with key customers relates to variation in the valuation at a given round of financing).

Third, by understanding what needs to be learnt to persuade investors and the experiments that need to be run to generate this information, it also helps estimate the time and money that will be needed to generate the information needed to achieve the value inflection. This enables entrepreneurs to raise enough to achieve the next value inflection point, plus some extra cushion for unanticipated needs. Raising too much can lead to excess dilution while raising too little creates execution risk.

Fourth, realizing that it is investors' priors that are relevant highlights that there is path dependence in funding strategy. Raising money from certain early investors unlocks certain types of funding in the next stage but can also preclude an entrepreneur from raising funds from certain funds (due to the signal it sends those later-stage investors). Recognizing this allows entrepreneurs to be deliberate about building their investment syndicate.

Fifth, entrepreneurs may need to anticipate market downturns and plan appropriately due to the presence of financing risk. At times, it may make sense to try and raise more than is needed to protect a venture against a market downturn. This is true even if entrepreneur anticipates that the fundamentals of the venture itself will remain strong but believes that investors will be harder to persuade due to the increased financing risk.

4.2 Addressing the Challenges of Financing 'Deep Tech'

As discussed above, certain industries appear to face a natural handicap in terms of their attractiveness for venture capital. While there are many explanations for this, one that is relevant in the context of the framework above pertains to deep tech ventures that build on fundamental science and engineering. Several challenges make these types of ventures harder to commercialize. First, lab testing often occurs under very different conditions than would be seen in an actual commercial deployment at scale. Even when early experiments show promising results, those results are often less predictive of ultimate success than seeing early customer traction from a Minimum Viable Product in a software venture. What constitutes a successful result can be ambiguous due to a lack of well-established benchmarks and testing protocols that would allow for clear interpretation of experimental results and how they map to commercial viability, making it hard to update priors.

Given the importance of these technologies for addressing global challenges faced by society, overcoming these barriers will likely require a multi-pronged approach. Prior work has documented how policy makers who provide non-dilutive financing for such ventures to a point where there is clear value inflection can help unlock venture capital (Howell 2017). The framework above also sheds light on the promise of developing ways to develop greater confidence in the predictions of early experiments for ultimate success. It also highlights the importance of investors with specialized expertise in understanding and interpreting these signals, as well as programs that can support pre-commercial development of ventures towards addressing the specific concerns that early stage investors have about the ventures (Lerner 1999; Howell 2017, 2020).[8] Doing so can reduce frictions in the persuasion challenge faced by deep tech entrepreneurs.

[8]This can often relate to the ability of the management team to execute, something that entrepreneurial teams under-emphasize in their assessment of the risks to the venture's success.

5 Conclusion

As the 'Bayesian Entrepreneurship' research agenda develops, my hope is that entrepreneurship scholars continue to work on integrating these streams of related work to make the power of this framework clear. Otherwise, it risks remaining niche and fragmented. For example, Agrawal et al. (2024) explicitly define Bayesian entrepreneurship as having heterogeneous priors and in fact, going to the point of noting that having shared priors is *not* Bayesian Entrepreneurship. This seems to me to be an unnecessarily strong exclusion criterion and one that reduces the scope for learning across related literatures. I would suggest that instead, like many other research stream including economics, this literature develops a perspective that Bayesian Entrepreneurship is not *necessarily* about homogeneous priors. This is because starting with homogenous priors is a weaker assumption and therefore requires a higher hurdle to generate desired results. It will also allow scholars to understand in which instances heterogeneous priors are critical to generating insights that common priors cannot and heterogeneous beliefs might evolve in the first place (Acemoglu, Chernozhukov, and Yildiz 2006; Nimark and Sundaresan 2019). Relatedly, it would be valuable to ensure that a shared language is used when defining disagreement between entrepreneurs and other stakeholders, in particular distinguishing between statements such as stronger vs. weaker priors and optimism vs. pessimism. This will allow for greater communication between literatures and enable greater cross-fertilization of ideas.

In conclusion, I have tried to highlight how the conceptual insights developed by Agrawal et al. (2024) chapter on Bayesian Entrepreneurship are closely related to a growing entrepreneurial finance literature on learning through multi-stage financing. I also highlight how such a 'learning perspective to staged financing' has strong pedagogical value because it helps provide a clear, actionable approach to navigating the process of financing highly uncertain new ventures. In turn, this enables a promising research agenda that can help both identify as well as quantify frictions to effective learning and the related solutions to more effectively persuading of investors about the potential of different ventures.

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Internet Appendix for
"Priors, Experiments, Learning and Persuasion in (Bayesian) Entrepreneurial Finance"

Figure 1: ***Mean of Amount Raised, Dilution and Exit Valuations across Industries***

This table reports values for all venture capital deals of firms incorporated in the US from 2013-2022. The data source is Pitchbook. The analysis excludes rounds with missing valuation or deal size, and rounds that follow a missing round and only consider rounds upto Round 5. Hardware companies are classifiedd as those manufacturing computer hardware; manufacturing and distributing communication equipment or providing communication services; manufacturing and designing semiconductors and circuits; or providing energy-related products. MedTech companies are defined as those manufacturing healthcare devices and supplies for consumers and other healthcare organizations. Pharmaceuticals companies are defined as those engaged in drug discovery and delivery of pharmaceuticals or biotechnology. Software companies are defined as those that design and develop software for both business and consumers.

Industry	Amount Raised	Dilution	Pre-money	Stepup Multiples	Exit Valuation
Round 1					
Hardware	5.22	26.29	12.76		
MedTech	5.31	29.16	10.20		
Pharmaceuticals	20.37	40.93	24.10		
Software	3.52	22.79	11.74		
Round 2					
Hardware	14.35	24.89	52.41	4.08	104.85
MedTech	10.24	25.30	29.17	2.91	416.58
Pharmaceuticals	43.49	32.65	103.36	3.18	530.69
Software	10.26	22.85	43.75	5.25	44.96
Round 3					
Hardware	23.96	21.22	106.57	1.91	137.98
MedTech	19.88	25.14	60.08	2.08	174.29
Pharmaceuticals	59.06	26.46	225.31	1.91	457.09
Software	19.82	20.45	108.35	2.78	169.58
Round 4					
Hardware	40.16	18.85	253.92	1.80	168.25
MedTech	31.47	22.30	113.71	1.61	N/A
Pharmaceuticals	60.60	23.88	226.33	1.93	468.64
Software	38.82	18.28	258.02	2.27	132.15
Round 5					
Hardware	91.88	16.22	529.18	1.61	302.86
MedTech	23.86	17.44	115.79	1.23	N/A
Pharmaceuticals	60.26	20.57	306.72	1.46	1160.76
Software	71.04	16.25	588.24	2.08	362.44

Amounts raised are in USD million for non-exit deals. Dilution represents the percentage of shares acquired in a non-exit deal. Pre-money valuation is in USD million for non-exit deals. Step-up multiples are defined as $Stepup_t = \frac{PreMoney_t}{PostMoney_{t-1}}, t = 2, 3, ...$ Exit valuation is the pre-money valuation of exit deals (i.e., MA or IPO) in USD million. Round t refers to the exit valuation of firms that raised $t-1$ round(s) of private financing before exit.

Figure 2: ***Median of Amount Raised, Dilution and Exit Valuations across Industries***

This table reports values for all venture capital deals of firms incorporated in the US from 2013-2022. The data source is Pitchbook. The analysis excludes rounds with missing valuation or deal size, and rounds that follow a missing round and only consider rounds upto Round 5. Hardware companies are classifiedd as those manufacturing computer hardware; manufacturing and distributing communication equipment or providing communication services; manufacturing and designing semiconductors and circuits; or providing energy-related products. MedTech companies are defined as those manufacturing healthcare devices and supplies for consumers and other healthcare organizations. Pharmaceuticals companies are defined as those engaged in drug discovery and delivery of pharmaceuticals or biotechnology. Software companies are defined as those that design and develop software for both business and consumers.

Industry	Amount Raised	Dilution	Pre-money	Stepup Multiples	Exit Valuation
Round 1					
Hardware	2.22	25.93	7.00		
MedTech	2.00	27.92	5.01		
Pharmaceuticals	6.50	39.14	10.00		
Software	1.80	23.08	5.90		
Round 2					
Hardware	8.50	24.70	25.00	2.57	11.54
MedTech	5.00	23.95	17.38	1.71	380.81
Pharmaceuticals	20.05	30.77	40.00	1.94	198.49
Software	5.28	22.48	19.00	2.34	20.55
Round 3					
Hardware	15.18	22.56	50.00	1.53	72.80
MedTech	8.19	23.51	30.00	1.37	120.00
Pharmaceuticals	38.50	23.50	100.00	1.43	288.14
Software	11.00	19.64	40.00	1.87	64.75
Round 4					
Hardware	28.48	18.36	122.93	1.66	100.00
MedTech	12.00	21.85	41.00	1.31	N/A
Pharmaceuticals	37.00	21.66	149.16	1.27	374.45
Software	20.00	16.28	90.00	1.76	75.03
Round 5					
Hardware	50.00	14.37	236.00	1.24	302.86
MedTech	12.60	15.16	57.75	1.34	N/A
Pharmaceuticals	34.89	15.17	207.45	1.11	460.54
Software	39.93	13.28	215.00	1.71	236.70

Amounts raised are in USD million for non-exit deals. Dilution represents the percentage of shares acquired in a non-exit deal. Pre-money valuation is in USD million for non-exit deals. Step-up multiples are defined as $Stepup_t = \frac{PreMoney_t}{PostMoney_{t-1}}, t = 2, 3, ...$ Exit valuation is the pre-money valuation of exit deals (i.e., MA or IPO) in USD million. Round t refers to the exit valuation of firms that raised $t-1$ round(s) of private financing before exit.