A structural model of mentorship in startup accelerators: Matching, learning, and value creation
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Abstract

Entrepreneurial success depends on reducing uncertainty about the quality of ideas and selecting effective strategies to bring the idea to market. Mentorship plays a critical role in this process. In this paper, I examine how mentorship improves entrepreneurial outcomes within the Creative Destruction Lab (CDL), a global mentorship-driven startup accelerator, through two channels: the direct effect of improving startup quality and the screening effect of identifying high-quality startups. Using mentorship interaction data from CDL, I apply machine learning algorithms to generate quantifiable measures of mentors' advice. I propose and estimate a structural model of mentorship, where the dynamics of quality accumulation are influenced by both the direct effect of mentors' advice and the screening effect from mentors' learning. I find that mentorship generates value through both direct and screening effects, with significant spillovers of quality signals between mentors. This model enables a counterfactual analysis, quantifying the value added by mentors when they actively shape the strategic direction of startups, compared to a more passive role where they support the execution of the entrepreneurs' original plans. The counterfactual analysis shows that entrepreneurs benefit from mentors' strategic guidance, with significant heterogeneity across sectors. In emerging sectors like quantum, mentors' strategic input has minimal impact, especially early on, suggesting that a more passive mentorship approach may be more beneficial. In these sectors, screening gains grow over time as mentors accumulate information and provide guidance that better reflects the true quality of the startups. These results offer important managerial implications for the design of intermediaries, such as accelerators that provide mentorship, suggesting that guidance approaches should be tailored to the specific needs and developmental stages of each sector.

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1 Introduction

To commercialize their ideas, entrepreneurs must choose between multiple potential strategies and their success depends on both having an idea that delivers real value and the effectiveness of the chosen strategy (Sevilla-Bernardo et al. (2022),Agrawal et al. (2021)). However, they face uncertainty about both of these dimensions which results in demand for experimentation (Murray and Tripsas (2004); Ries (2011); Kerr et al. (2014); Chavda et al. (2024)). This experimentation process involves designing tests to evaluate the viability of their ideas and to identify the most effective strategies for implementation.

Recent theoretical work (Agrawal et al. (2021)) highlights the role of advice provided by investors, industry experts, and mentors in reducing the costs of experimentation and guiding entrepreneurs in their decision-making processes. Institutions that offer this guidance can significantly improve entrepreneurial outcomes by making the decision-making process more efficient. Advice creates real value by lowering the cost of experimentation for entrepreneurs through optimal sequencing and the types of tests they implement. Startup accelerators[1] are among these institutions that can improve entrepreneurial outcomes by providing mentorship and valuable advice to *enable entrepreneurial choice* (Agrawal et al. (2021)). The success of an idea then depends on entrepreneurs capacity to attract resources including advice from others (Stevenson (1983)). So, resolving the uncertainty around the quality influences the allocation of resources including mentorship to entrepreneurs (Agrawal et al. (2024), Yu (2020)).

In this paper, I first explore the mechanisms through which mentorship improves entrepreneurial performance within a mentorship-driven accelerator program, Creative Destruction Lab (CDL). Specifically, it investigates two key mechanisms. The direct effect of improving startup quality, and the screening effect of identifying high-quality startups. The direct effect captures the quality improvement in startups through mentor advice and support. The screening effect explores how mentors' evaluations of startups evolve over time as they gather more information about the startup's potential. This learning process enables mentors to allocate their efforts and resources more effectively, focusing on startups that show promise. I then focus on mentors strategic guidance and separate it from other forms of support they provide and quantify the value added of mentors' strategic guidance.

Addressing the research questions in this study is challenging for several reasons. One challenge is identifying the impact of mentorship. Mentors evaluate startups through sequential interactions, yet detailed data capturing how mentors update their evaluations is often missing. The literature on staged financing by venture capital (VC) investors suggests that staged investment adds value by giving investors the option to stop funding based on updated information (Tian (2011), Bergemann and Hege (1998)). Similarly, understanding the real option value of mentorship requires observing sequential interactions. However, the lack of detailed, sequential data on mentorship interactions has limited the empirical literature to fully explore this mechanism.

[1]An accelerator is a "fixed-term, cohort-based program for startups, including mentorship and/or educational components, that ends with a graduation event or demo-day. These programs aim to accelerate the growth of startups by providing resources, mentorship, and networking opportunities." (Cohen et al. (2014)).

A second challenge is that mentorship is subject to selection bias. The correlation between mentorship and startup's performance is the result of two potential factors: selection, where mentors choose to mentor startups with higher ex-ante potentials, and the causal effect of mentorship on performance. To address this endogeneity issue, other empirical work has used several instrumental variables or designed experiments to isolate the causal effect of mentorship on performance. Advice implementation can also be endogenous, as higher-quality startups may be better at implementing advice. I leverage the exogenous interactions between mentors and startups that occur before formal mentorship allocations in the CDL program, along with the random availability of mentors due to personal scheduling conflicts, as instrumental variables to isolate the causal effect of mentorship interactions and advice implementations on startup performance.

Third challenge lies in distinguishing between different types of advice, as not all mentorship interactions are the same. The value of mentorship can vary depending on whether the advice fundamentally changes an entrepreneur's strategy or just helps with facilitating an existing plan. Accurately assessing the impact of advice requires knowing what the entrepreneur's strategy would have been without mentorship, which is often unobservable. In practice, we often only see the final implemented plan, which could be a result of the entrepreneur's original idea, the mentor's influence, or a combination of both. The challenge is that we cannot usually observe what the entrepreneur's original plan would have been in the absence of mentorship, making it difficult to determine the true impact of the mentor's guidance on strategic decision-making.

A distinctive feature of the Creative Destruction Lab (CDL), where entrepreneurs propose initial plans and mentors finalize alternative ones, provides the data that would otherwise be unobserved, allowing me to measure the advice on entrepreneur's original plans. By estimating a structural model that accounts for the endogenous implementation of advice, I conduct a counterfactual analysis to simulate what the outcomes would have been if entrepreneurs had received support in executing their original plans, without mentors intervening to change the strategic direction.

To analyze the unstructured text data on entrepreneurs' chosen objectives and the mentors' advice on those objectives, I use generative AI tools such as the Cohere API for unsupervised text classification (topic modeling), zero-shot classification, and few-shot classification, along with traditional models like LDA. These methods help me categorize the objectives set by entrepreneurs and the corresponding advice provided by mentors and to measure the advice on entrepreneurial decisions. Cohere provides a Large Language Model (LLM) (Generative AI models) that are designed to handle complex language understanding tasks with high accuracy. Using this categorization of plans and advice, I measure the differences between mentor-proposed and startup-proposed plans. If the alternative plan suggested by mentor differs from the original plan, I consider this as an advice that changes the entrepreneurs direction.

To investigate these channels, it is essential to capture the dynamic interactions between mentors and entrepreneurs, including how mentors select which entrepreneurs to guide, how they refine their selections based on ongoing learning, and how entrepreneurs decide whether to implement the advice provided by mentors. This motivates the development of a structural model that incorporates the dynamics of mentors selection, the learning process of mentors, and the endogenous decisions of entrepreneurs to implement the advice they receive. To capture the mentors' learning, I need to disentangle the value of mentorship in resolving mentors' uncertainty about the quality from the direct impact of mentorship on improving the quality itself. For the entrepreneur's plan channel, I need to conduct a counterfactual analysis to simulate what the outcomes would have been if mentors had helped entrepreneurs implement their original plans rather than suggesting alternative strategies. A structural model allows for modeling these endogenous decisions of mentor selection and advice implementation within a dynamic framework, capturing the iterative learning process and quality accumulation.

I propose a dynamic structural model of incomplete information where mentors, who are uncertain about the quality of the startups, choose which startups to mentor over multiple sessions. Entrepreneurs then decide whether to adapt and implement the advice they receive. The quality accumulates as a result of both mentorship interactions and advice implementations. Their willingness to implement advice varies depending on the nature of the task and whether the objective aligns with their original plan. I estimate the model using detailed data from the Creative Destruction Lab (CDL), a global mentorship-driven startup accelerator, complemented with the Crunchbase data to obtain data on startups' post-CDL performance. I measure the final quality (performance) of startups by the logarithm of the funding raised within one year after CDL attendance.

I find that mentorship generates value through both the direct effect and the indirect effect. In the direct mechanism, I find that mentorship improves the quality of startup by 67% through advice implementation and by 25% through other mentorship benefits that are not captured in the advice implementation. In the screening mechanism, I find that through mentorship interactions, mentors learn about the startups' potential and can identify higher-quality ones for subsequent mentorship allocation. These results suggest that mentorship not only directly improves startup quality but also plays a key role in reducing uncertainty about the potential of entrepreneurial ideas.

My learning model estimates reveal that mentors update their beliefs about a startup's unobserved quality at a slow rate. Since screening depends on both observable outcomes of mentorship and signals from the startup's unobserved quality, this slow learning rate means that mentors rely heavily on observable progress and outcomes from implemented objectives to make decisions. As a result, the objective-setting process and the effectiveness of these objectives play a crucial role in helping mentors distinguish high-quality startups.

To capture the dynamics of learning gains across multiple sessions, I conduct a counterfactual analysis by sequentially omitting sessions from the CDL program and evaluating the specific gains attributed to each session. This approach allows me to quantify the contribution of each session to the overall mentorship outcomes. I find that learning gains from mentorship tend to decrease over time in most sectors, with the largest gains occurring during the initial interactions. However, in emerging sectors, the learning process is slower and gains increase gradually, indicating that in less explored areas, it may take longer or be more difficult to differentiate between high-quality and low-quality ideas.

For mentors in the program, the implementation of mentor-driven objectives by entrepreneurs serves as an observable outcome of mentorship. If mentors believe that successful implementation indicates higher startup quality, then screening gains depend significantly on the relevance and effectiveness of the objectives set. The increasing learning gains in uncertain environments suggest that mentors may initially provide less effective advice, resulting in observable outcomes that are less indicative of the startup's true quality. Over time, however, as mentors gather cumulative signals through repeated interactions, they adjust their objectives to more accurately reflect the startup's actual quality.

In the value of mentors' strategic guidance, I conduct a counterfactual experiment to simulate the entrepreneurial outcomes when mentors' advice is replaced with the entrepreneur's original proposed objectives. This intervention can be interpreted as mentors helping with the implementation of the entrepreneur's objectives, rather than guiding them to select and prioritize tasks. This simulation quantifies the gains from mentors' influence on changing the direction of the entrepreneur's choice. The implications of such an intervention are ambiguous, as it is unclear whether the entrepreneurs' proposed tasks are less costly to implement and because entrepreneurs might respond differently when executing a task that differs from their original choices. In a broader view, the experiment quantifies the additional value generated through shaping the entrepreneurial strategy. I find that mentors' input on the objectives set by entrepreneurs improves the gains from mentorship, with the average entrepreneur benefiting from this advice.

I find heterogeneous gains from advice on entrepreneurial strategy across different sectors. sectors with higher gains such as fintech show that startups in these areas benefit more from advice on their decisions. Other sectors such as quantum gain less from advice on entrepreneurs choice. This might be due to the specialized nature of these fields, where the challenges and decision-making processes require more technical expertise and knowledge.

The rest of the paper is structured as follows. Section 2 discusses the related literature and contributions of this paper. Section 3 provides institutional details of the Creative Destruction Lab. In Section 4, I describe the data used and present descriptive evidence of mentorship effects. Section 5 outlines the structural model of mentorship, and Section 6 explains the estimation and identification strategy. Section 7 presents my results, and Section 8 concludes.

2 Literature Review

Mentors help entrepreneurs refine their strategies, which can improve the entrepreneurial choice. To study the effect of advice on entrepreneurial choice, helping entrepreneurs make better decisions and guiding their strategic direction, empirical literature has focused on how receiving advice affects the startup's performance or subsequent choices such as market entry decision, hiring decisions, etc (Aaron et al. (2019), Yu (2020), Sariri (2020), Sariri (2022)). For instance, Aaron et al. (2019) conduct a randomized field experiment to explore the effect of advice on managing the employees on startup's performance. They find that entrepreneurs who received management advice perform better and are less likely to fail.

Mentors choose which entrepreneur to guide based on their evaluation of the quality of the startup. Expert's initial evaluations then plays a critical role in the allocation of advice as these priors determine which ideas receive more attention and resources Scott et al. (2020). The literature on accelerators documents that these organizations do not accurately assess the quality of the startups that apply to these program (Gans et al. (2008); Kerr et al. (2014); Luo and Sahni (2014)), particularly those startups from foreign countries (Wright et al. (2023)), due to a lack of information necessary to identify promising ideas. Moreover, evaluators may have biases for gender, race, and expertise in various entrepreneurial and innovation contexts (Hegde and Tumlinson (2014); Lee and Huang (2018); Li (2017); Niessen-Ruenzi and Ruenzi (2019)). Sequential interactions can help refine these evaluations, mitigate initial biases and ultimately adjust their resource allocation more effectively.

This paper primarily contributes to the literature on the role of experimentation on entrepreneurial ecosystem (Agrawal et al. (2024), Agrawal et al. (2021), Kerr et al. (2014)) and the effect of advice on entrepreneurial outcome (Lee et al. (2024), Aaron et al. (2019), Otis et al. (2023), Eső and Szentes (2007)). To the best of my knowledge, this paper is the first to develop and estimate a structural model with endogenous mentorship allocation that disentangles and quantifies different channels through which mentorship and advice improve entrepreneurial outcomes. Entrepreneurial ventures should be viewed as a series of experiments (Kerr et al. (2014)). Technological advancements such as the emergence of the Internet, cloud computing, the rapid rise of angel investors and crowdfunding platforms have significantly lowered the costs of running experiments in entrepreneurship. These developments have also transformed the financing environment (Ewens et al. (2018)) and also resulted in different types of cohort-based accelerator programs with educational components. This paper contributes to this literature by providing empirical evidence on how accelerators lower the cost of experimentation, helping the identification of high-quality ideas through a dynamic learning process, and helping entrepreneurs refine their strategies.

Accelerators have significantly changed how new ventures are supported and developed (Cohen et al. (2014)), with studies showing their positive impact on entrepreneurial outcomes (Hallen et al. (2020), Yu (2020), Cohen et al. (2014)). Graduating from an accelerator serves as a quality signal to the market (Kim and Wagman (2014)), enabling investors to evaluate startups more closely before making financial commitments (Radojevich-Kelley and Hoffman (2012), Kim and Wagman (2012)). While most literature aggregates data from multiple accelerators to examine their overall effectiveness (**?**, Hochberg (2016), Hallen et al. (2020), Cohen et al. (2019), Yu (2020)), fewer studies focus on the specific dynamics of mentorship interactions (Sariri (2020), Sariri (2022)). This gap exists due to limited data on these interactions and post-program outcomes (Hochberg (2016)). Using detailed mentorship data from CDL, I can identify the mechanisms through which mentorship improves entrepreneurial performance and quantify the incremental value created by accelerators.

This paper contributes to the literature on decision-making in firms (Goldfarb and Xiao (2011)) by providing empirical evidence on the value of human judgment in entrepreneurial decision-making. Recent work highlights the growing role of AI in decision-making (Otis et al. (2023), Agrawal et al. (2018b)). By estimating the value of mentors' advice, this study offers a framework to assess and compare the effectiveness of AI-generated advice, establishing a benchmark for human judgment in improving entrepreneurial strategy (Agrawal et al. (2018a)). Furthermore, this paper expands the entrepreneurial finance literature on the dual role of venture capitalists (VCs) as both selectors and mentors of startups. Prior research shows that VCs not only provide capital but also actively support their portfolio companies, leading to better decisions and increased innovation (Fu (2024), Bernstein et al. (2016), Gill et al. (2024), Ewens and Marx (2018), Bottazzi et al. (2008)). My findings contribute to this by providing evidence on the value of advice in shaping firms' strategies (Baum and Silverman (2004)).

Lastly, this paper adds to the literature on dynamic structural models in the entrepreneurial ecosystem (Sørensen (2007), Nanda and Rhodes-Kropf (2017), Ewens et al. (2018)), Sørensen (2007) develops a matching model to separate the effect of sorting from the true impact of venture capital on the value of the companies they invest in. Nanda and Rhodes-Kropf (2017) develop an investment model under uncertainty that explores how investors' decisions in financing new ventures are influenced by the risk of future funding constraints and show how financing risk leads investors to shift their focus away from more innovative firms with higher real option value, potentially impacting the success and diffusion of novel technologies. Methodologically, my paper is close to the literature on the estimation of dynamic structural models (Hotz and Miller (1993),Aguirregabiria and Mira (2010), Aguirregabiria and Mira (2007)).

3 Creative Destruction Lab (CDL)

3.1 Introduction

Creative Destruction Lab (CDL) is a leading global entrepreneurship program that provides for early-stage, science-based startups. It was founded by Professor Ajay Agrawal at the University of Toronto's Rotman School of Management. The first program in 2012 was an experiment to use an objective-setting model to support technical founders at the beginning of their startup journey. The success of this early program led to the expansion of CDL to multiple global locations and multiple specialized streams of focus.

CDL provides a setting where entrepreneurs seek business support from mentors to build and scale their technology-based company. The program has an objective-based mentoring process where experienced business experts, investors and scientists provide mentorship through objective-setting. These mentors work closely with the startups to help them refine their business models, develop their technologies, and secure funding. The main idea behind the CDL program is that the biggest problem in turning excellent science and innovation into successful businesses is a failure in the market for judgment. The 'market for judgment' is a scenario where mentors who have the knowledge (judgment) can set and prioritize goals for less experienced entrepreneurs. The main goal of CDL was to bridge the gap between scientific innovation and market success, helping startups transform breakthrough technologies into commercially viable products and services. To achieve this goal, CDL helps startup founders to prioritize tasks that efficiently and effectively mitigate risks and increase their probability of success. The organization focuses on setting clear, measurable objectives to help startups sharpen their strategic focus, prioritize resources, and achieve rapid, sustainable growth.

3.2 Expansion

Since 2012, CDL has expanded from a single site in Toronto to multiple global sites, including Vancouver, Calgary, Montreal, Halifax, Oxford, Paris, Atlanta, Wisconsin, Berlin, Estonia, Melbourne and Seattle. Each CDL location operates a number of specialized streams that focus on different market needs, using local expertise and resources. These streams focus on different areas such as Artificial Intelligence, Quantum Computing, Health Sciences, Energy, Space, Blockchain, and more. The program is designed to provide targeted mentorship and resources to startups within these specialized sectors. Figure 1 shows the trend of number of sites and number of streams since 2012. Figure 2 shows the introduction of new streams over the years and also the share of accepted startups in each stream.

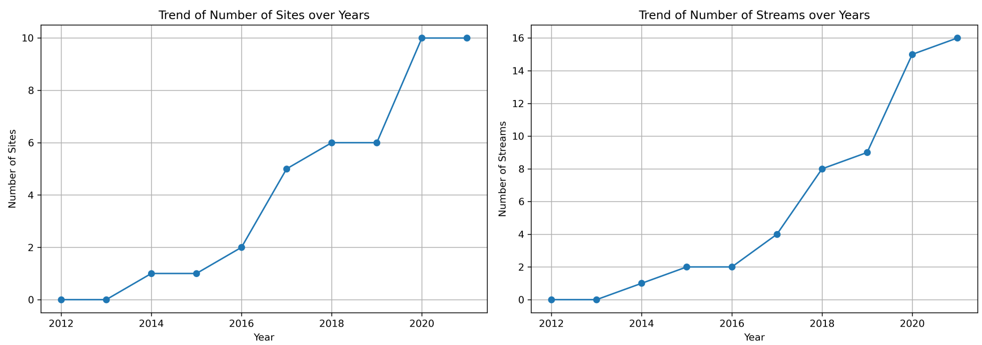


Figure 1: The trend in the number of sites and streams at the Creative Destruction Lab.

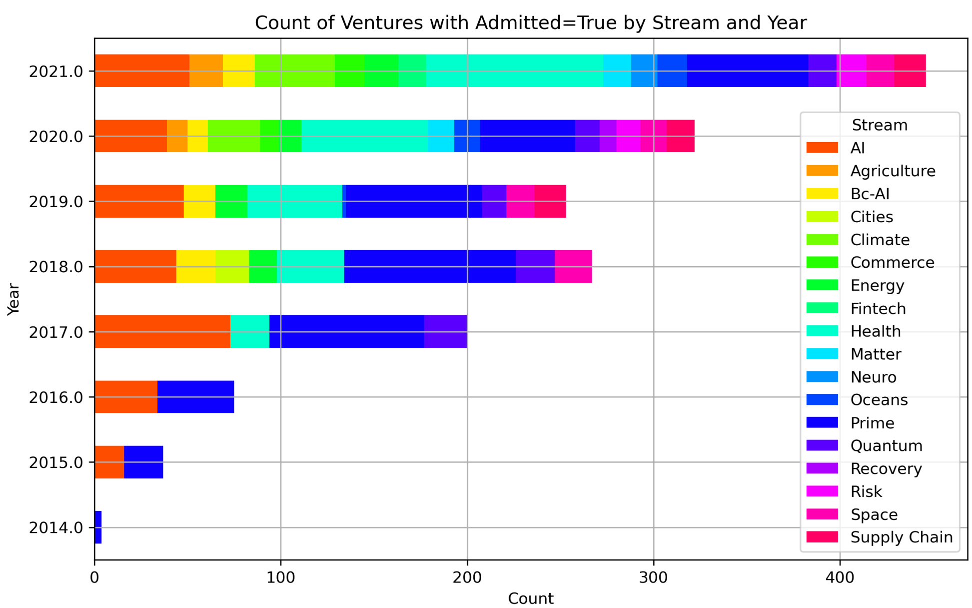


Figure 2: Introduction of new streams at the Creative Destruction Lab over the years and the distribution of accepted startups across each stream.

Number of total accepted startups has increased from around 20 startups in 2012 to around 600 startups in 2021. Figure 3 shows the trend of total startups that has applied to the CDL and the trend of admitted startups.

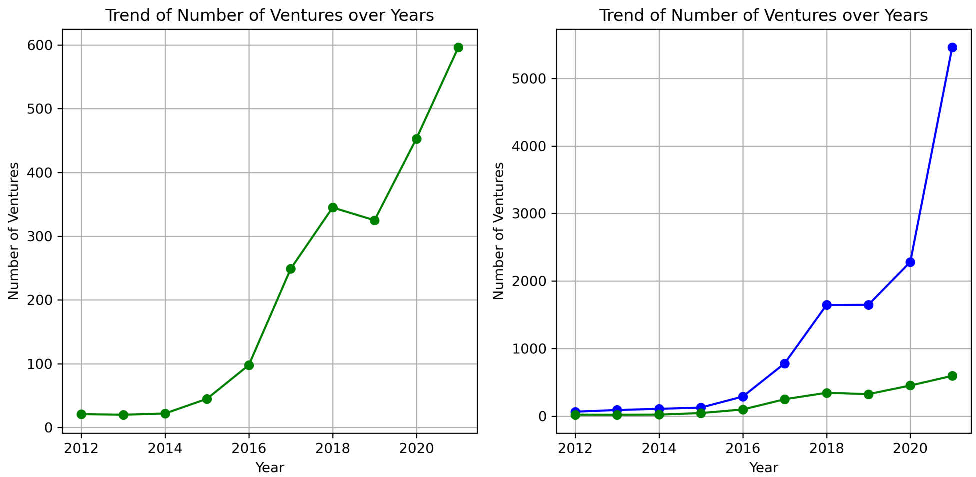


Figure 3: rends in the total number of startups that have applied to the Creative Destruction Lab and the number of startups admitted.

3.3 Program Setting

Every year, startups apply to participate in the CDL program by submitting an application that outlines their business idea, technology, and growth potential. Each cycle of the program lasts one year. The CDL admissions team reviews the applications, and startups are admitted into their respective streams at each location. Upon admission into the program, all startups attend public objective-setting sessions every eight weeks, where mentors provide technical and business guidance.

Mentorship Sessions: Each cohort has four or five meetings throughout the year. In some years, depending on the site and stream, there are either four or five sessions. At the first session, startups present their ideas, current progress, and challenges to the mentors in attendance. Each startup proposes three main objectives to be implemented by the next session (in eight weeks). All mentors engage in a discussion to revise, refine, and finalize the objectives for each startup. After all the startups have presented, the founders leave the meeting, and the mentors discuss their thoughts on the different startups. Then, each mentor present at the meeting decides whether they want to formally mentor a particular startup until the next session. If a mentor decides to take on a startup, they commit to spending four hours of private mentorship time with the founders to help achieve the finalized objectives. If a startup does not attract any mentorship interest, it will be removed from the program and will not attend the next sessions.

In the subsequent session, all startups and mentors meet again. Each startup's previous mentors provide feedback on the startup's progress and recent activities. The startups then present their latest updates, challenges, and outline three objectives for the upcoming session. The mentors collaboratively review and finalize these objectives for each startup. After all presentations are complete, the founders leave the room, allowing the mentors to decide which startups they will commit four hours of mentorship to. Mentors are free to choose whether to continue with the same startups or switch to different ones. Each startup may be supported by more than one mentor, and mentors can select multiple startups to guide. This selection process is repeated in each session throughout the program. If a startup fails to secure any mentorship interests during a session, it is eliminated from the program and will not graduate from CDL.

Figure 4 shows an example of a progress report presented at the beginning of each session. This report includes the outcomes of the objectives from the previous session, indicating whether they were implemented. It also details three new objectives proposed by the founders for the next two months, along with positive updates and challenges reported by the CEO. During the public meeting, all mentors review the achievements of the previous objectives. Previous mentors share their insights on the startups, and then all mentors work together to revise and finalize the proposed objectives. Figure 5 shows a real example of proposed objectives and their finalized versions. Some founders proposed a first priority objective that is very similar to the objective finalized by mentors. However, some founders proposed objectives that mentors did not consider a priority, and these were changed.

At the first public session, startups present their ideas, current progress, and challenges to all the mentors in the room. Each startup proposes three main objectives to be implemented by the next session in eight weeks. All mentors engage in a discussion to revise, refine, and finalize the objectives for each startup. at this stage, mentors collaboratively provide strategic guidance and actively intervene in the strategic direction of entrepreneur. After all the startups received their finalized objectives by mentors, the founders leave the meeting, and then mentors choose wether they want to mentor a particular startup until next meeting. Mentors who choose to mentor a startup, should spend 4 hours of mentorship hours with the founders and help them achieve the finalized objectives.

In the subsequent session, all startups and mentors meet again in the next public meeting. Entrepreneurs present their ideas, current progress, and challenges to all the mentors in the room. Each mentor provides additional information on the progress and recent activities of their mentee to everyone in the room. this is how mentors share their private information that they might have received with other people in their room. The startups then propose three new objectives for the next session. All mentors in the room discuss and refine and finalize these objectives for each startup. The founders leave the room, mentors decide which startups they will commit four hours of mentorship to. Mentors are free to choose whether to continue with the same startups or If a startup fails to secure any mentorship interests during a session, it is eliminated from the program and will not graduate from CDL.

In the following sessions the cycle repeats and the program proceeds to the final session. At the final session of the program, entrepreneurs again present their progress and their mentors share information with others. Then at this session mentors decide wether a startup should graduate from the program or not. A startup graduates if at least one mentor thinks that startup should graduate. The questions that mentors consider when choosing a startup to graduate include:

- Does the venture have the potential to be massively scalable?
- Have they made meaningful progress during the program?
- Have they demonstrated a clear ability to execute?

Figure 6 illustrates an example of a program with 3 sessions. The objective setting process happens collaboratively before the mentorship allocation choices made by each mentor. Here, in the second session, mentors have updated their choices and Mentor 2 decided not to continue with startup B and no one else is willing to mentor this startup. In the next session startup B will be removed from the program and does not attend the next meeting. In session 2, again new set of objectives are proposed by entrepreneurs and finalized by mentors. Mentors then update their choices about private mentorship hours. In session 3 (final session in this example), the whole cycle repeats and the mentors choices determine the graduates of the program. In this example, only startup C will graduate.

Small Group Meetings (SGMs): One aspect of the program involves organizing Small Group Meetings (SGMs) just before each public session. During these SGMs, each startup has private meetings with a set of mentors. The program assigns these mentors to the startups; it is not up to the mentors to choose. Typically, startups are paired with mentors they have worked with before, as well as new mentors they haven't previously engaged with. During these small meetings, startups meet with around 20% of all mentors, and more than 80% of these mentors they meet have not previously engaged with those startups. These SGMs create an environment where startups can benefit from the insights of mentors who did not specifically choose them, and also give mentors an opportunity to better understand and assess the startups.

CDL-TORONTO Session #4: [redacted] ([redacted], CAN)

CREATIVE DESTRUCTION LAB

COMPANY WEBSITE: [redacted]
CO-FOUNDERS: [redacted] (CEO), [redacted] (COO)
STREAM: Prime
This document updates the Venture's progress since the last Session. For additional information, see the Venture Overview.

VENTURE DESCRIPTION

[redacted]

CDL JOURNEY

Session 1
- *Mentor(s):* [redacted]
- *Recommendation:* [redacted]

Session 2
- *Mentor(s):* [redacted]
- *Recommendation:* [redacted]

Session 3
- *Mentor(s):* [redacted]
- *Recommendation:* [redacted]

Session 4

PROGRESS ON OBJECTIVES SET AT THE PREVIOUS SESSION

1. Achieve $250K USD in monthly revenue. **(INCOMPLETE)**
2. Hire six production staff. Begin renovations for expansion into an additional 6,000 sq ft. **(COMPLETE)**
3. Get product on [redacted] **(INCOMPLETE)**

PROPOSED 2-MONTH OBJECTIVES

1. Raise Series A.
2. Continue to grow revenue to over $250k in June.
3. Put in place better order/operations system to [redacted]

CEO UPDATE

What is going well?
- [redacted]
- Receiving great customer feedback.

What are the biggest challenges?
- Keeping up with orders.

CDL COMMENTARY BY RACHEL HARRIS (VENTURE MANAGER)

1. [redacted]
2. [redacted]

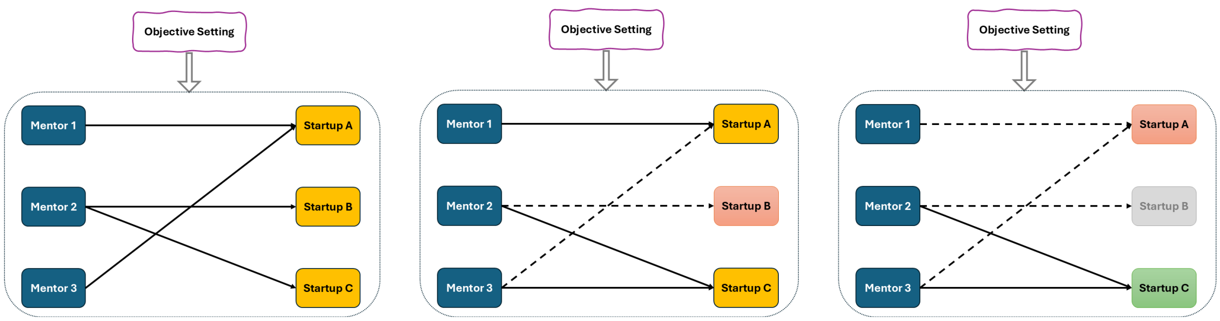
FINANCING UPDATE

Current Monthly Burn (gross):	$[redacted]K
Runway:	[redacted] months
Total Amount Raised:	$[redacted]M USD
Current Employee Headcount:	[redacted] FTE
Amount Raising (if raising):	$[redacted]M USD, [redacted]
Revenue:	$[redacted]K USD [redacted]
CDL-Affiliated Investors:	[redacted], [redacted], [redacted], [redacted]

Figure 4: Example of a progress report presented at the beginning of each session, detailing the outcomes of previous objectives, new objectives proposed for the next two months, and updates on successes and challenges from the CEO.

	cohort	site	stream	session	venture_id	proposedobjective1	finalizedobjective1
0	2021	5	1	2	7256	Establish product trials at three Canadian hospitals including a major Ontario hospital.	Obtain FDA registration as a Class 1 Medical Device
1	2020	1	3	1	7402	Choose a business plan and a customer segment for their beachhead	Choose a business plan and a customer segment for beachhead, and define their focus of efforts for development and sales between being therapeutics and drug discovery (
2	2017	2	1	2	1706	Demonstrate to more than three market influencers (key customers in the professional sport market) and attain letters of intent to endorse, product test and/or gather athletic data to build our database	Update the company's milestones and define the development, features (including analytics) and commercial deliverables through to product launch (Complete)
3	2019	1	1	1	4038	Get the venture's new manufacturing facility running at full capacity.	Connect with prospective partners in the Canadian ecosystem who are experts in various fields: a) immigration b) investors/angel investor c) plastic suppliers (Complete).
4	2018	2	1	3	1909	Close $10M CAD raise with right capital partners.	Close $10M CAD raise with right capital partners (Incomplete).
5	2018	2	3	3	1932	Raise $1M-$1.5M CAD.	Detail costs, timing and strategy to hit key short-term milestones including additional efficacy and distribution studies prior to entering scale-up manufacturing and toxicology studies (Incomplete) - Anticipated completion by Session 4.
6	2021	11	3	2	12491	Finalize GTM plan for 3x top line growth in 2022 with a recurring revenue addition.	Finalize GTM plan for 3x top line growth in 2022 with a recurring revenue addition.
7	2020	1	2	3	8118	Sign 3-5 additional clients, including diversity between large and small financial institutions to understand where scale can be achieved (client type, region, use case type etc.)	Conduct outreach to a wide variety of potential POC partners (at least three categories, e.g. SAAS partner to banks, US, bank, {8118} consulting shop). Close 1-2 POC clients.
8	2021	8	18	3	9242	Schedule meetings with five angel/strategic investors post end of March, following on from connections made in March.	Formalise a GTM strategy to answer the investor questions of "how can I help you" and "what will you do with the funding"
9	2016	1	2	1	519	Create an ML technology development roadmap.	Prepare competitive analysis of business and tech. (Complete)

Figure 5: Example of proposed objectives by entrepreneurs and finalized objectives set by mentors.



(a) Session 1 (b) Session 2 (c) Session 3

Figure 6: Example of the decision-making dynamics in a hypothetical 3-session mentorship program at CDL: (a) and (b) show the mentorship allocations chosen by mentors. (c) shows the graduation decision made by mentors.

4 Descriptive Analysis

4.1 Data and sample

Mentorship and Performance Data: In this paper, the CDL dataset is the primary source of data for analysis. Prior research has also explained the details of institution and data description for CDL (Sariri (2020), Sariri (2022), Sariri Khayatzadeh (2021), Lakhani et al. (2019)). I have the mentorship-interaction data for all the location and sectors from 8 cohorts: 2014 to 2021. Each cohort has four or five meetings throughout the year. Depending on the site and stream, there are either four or five sessions in each program. There are around 1800 startups and 1500 mentors in the final sample. I also observe the text data of all the proposed objectives by entrepreneurs at each session, as well as the text data on the final objectives that mentors finalize for each entrepreneur at each session. I also observe wether the final objectives of previous session has been implemented or not.

In addition to mentorship choices and advice implementations, the CDL dataset also includes information about the performance of most of the startups after the program. These information such as the startup business status, funding rounds and amount of raised fund are collected by CDL. I complement this data with Crunchbase dataset to include the funding data for all the startups that attend CDL.

Crunchbase is a comprehensive data portal for tracking financial and operational details of both public and private companies. This dataset contains companies information including their names, and their funding rounds. One notable aspect of Crunchbase is that it includes information about companies even if they haven't received VC investment. This sets it apart from some other financial databases that might only focus on companies with VC funding. As a result, Crunchbase provides a more comprehensive data to track the performance of startups in the market. I match startups on CDL dataset to the companies on Crunchbase dataset using company names. In cases where no post-program information is available for a startup in either the CDL or Crunchbase datasets, I categorize such startups as those that have raised zero funding. Table 1 provides summary statistics for the startups in my sample.

Table 1: Summary Statistics of Startups

	count	mean	std	min	25%	50%	75%	max
Total Funds Raised (1 Year)	1794.000	1604478.375	5307993.500	0.000	0.000	0.000	400000.000	72022960.000
Total Mentorships	1794.000	7.363	4.609	1.000	3.000	7.000	11.000	25.000
Total Unique Mentors	1794.000	5.480	3.318	1.000	3.000	5.000	8.000	23.000
Total Implemented Objectives	1794.000	4.247	2.874	0.000	2.000	4.000	6.000	17.000
Capital	1794.000	439257.099	1282392.318	0.000	0.000	1140.650	350000.000	20000000.000
Has Patent	1794.000	0.524	0.500	0.000	0.000	1.000	1.000	1.000
Has Prototype	1794.000	0.644	0.479	0.000	0.000	1.000	1.000	1.000
Number of Cofounders	1782.000	2.471	1.057	0.000	2.000	2.000	3.000	7.000
Learning to Plan	1794.000	-0.131	0.717	-3.000	-0.333	0.000	0.000	3.000
PhD/Professional Degree	1794.000	0.402	0.491	0.000	0.000	0.000	1.000	1.000

Advice Data: To analyze the large set of unstructured text data of mentorship advice, I first need to define a set of categories for the types of advice that are given to startups by mentors and then classify the text into these predefined categories. Sariri (2022) applies a manual classification process on a subset of the same data and develops a hierarchical typology of startup activities. He particularly focus on classifying the advice into product-market experimentation and business analysis activities. I on the other hand, focus on classifying the advice into different categories that represent the success factor of startups. I leverage generative AI tools to automatically define the categories and to categorize the data into those predefined classes. generative AI enhances scalability and ensures that the categorization process is both systematic and replicable across large datasets.

Initially, I need to define categories and perform a unsupervised text classification which is generally called topic modelling. I generated a set of categories using the ChatGPT model by OpenAI. this model leverages a large language model trained on a diverse range of text, which can suggest coherent and relevant business related categories of advice typically offered in startup mentorship contexts. I used different prompts such as "What are some common categories of advice that startup mentors provide? Group them into coherent and mutually exclusive categories", "Can you organize the common topics of advice given by startup mentors into business-related categories?",... to generate and validate different sets of actions that contribute to startups success. This approach is particularly useful when compared to topic modeling, which is often used to identify themes in text data but typically requires more post-processing to make the categories meaningful and distinct. While topic modeling, such as Latent Dirichlet Allocation (LDA), is a powerful tool for uncovering latent topics within a corpus, the categories it generates are not always directly interpretable without significant manual adjustment. Moreover, topic modeling generally requires to determine the number of topics in advance, which can lead to either very broad or small categories. I use other methods such as LDA abd sentence transformer models to generate topics and analyze the potential possible categories of the objectives.

The final categorization I use are 10 different categories based on the ChatGPT response and the literature on entrepreneurial activities (Sevilla-Bernardo et al. (2022), Bennett and Chatterji (2023)): Team Building and Hiring, Technology Development, Business Planning, Funding and Capital, Market Analysis, Prototype and Product Design, Sales and Marketing, Regulatory and Compliance, Intellectual Property, Data Management.

Zero-Shot Classification: Once these categories were defined, I used the Cohere classification model to systematically categorize the text data. Cohere uses Generative AI models, which are trained on large amounts of text data to understand language patterns, context to generate coherent and relevant text. These models are built using advanced machine learning techniques and are designed to handle complex language understanding tasks with high accuracy. By designing a prompt that asked the model to assign each piece of advice to the most appropriate category, I was able to automate the classification process. This process involves sending the advice text to the Cohere API, which then returns the most relevant category based on its pre-trained language models. This process is closely related to zero-shot classification where the model relies on its understanding of language and context to match input data with potential categories based on their descriptions or relationships. Zero-shot classification is a machine learning technique where a model is able to categorize or label data into classes that it has never seen before during training (Yin and Hay (2019), Puri (2019), Moreno-Garcia et al. (2023)).

Figure 7 shows the distribution of different categories for both proposed objectives and mentor-proposed objectives. Figure 8 presents two real examples illustrating how the binary variable of adjustment is measured. If the category of the entrepreneur-proposed objective matches the mentor's finalized objective, the adjustment measure for this advice is set to 0.

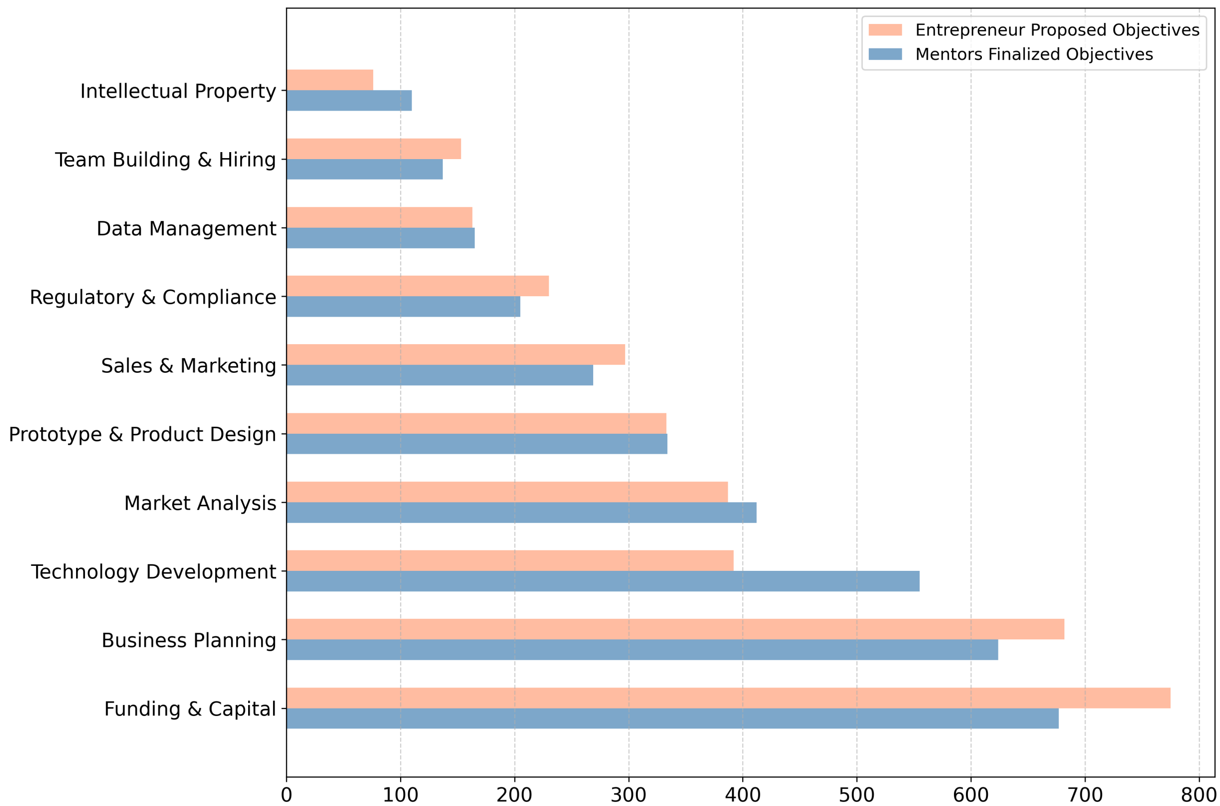
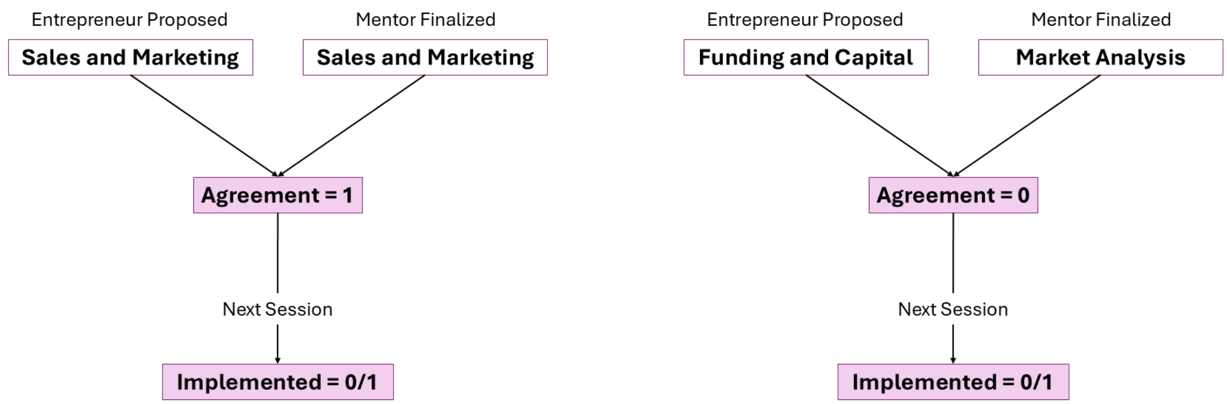


Figure 7: Distribution of advice classified into 10 different categories for both entrepreneur-proposed objectives and mentor-finalized objectives.

4.2 Reduced-Form Evidence

To motivate the model that captures the dynamics of the mentorship in the startup ecosystem, I present some preliminary evidence on the correlation between mentorship interactions and startup final quality.

I define measure of final quality as the logarithm of Post-CDL raised fund within 1 year from the CDL program. Figure 9 shows the distribution of performance (logarithm of raised fund after CDL+$1) for startups that graduates from CDL and startups that are cut from CDL through the process. Graduation is positively correlated with a startup achieving high quality, reflecting both selection effect and causal effect of mentorship on quality. This figure shows that there are still some startups that are cut from the CDL and



(a) Mentors do not change the entrepreneur-proposed objectives.

(b) Mentors change the entrepreneur-proposed objectives.

Figure 8: Two examples demonstrating the measurement of adjustment to the entrepreneur-proposed objectives by mentors. Adjustment is set to 1 when the categories match.

have relatively good final quality and there are some graduates of CDL that have low final quality.

Figure 10 shows the positive correlation between the logarithm of fund startups raise within one year after CDL and the total mentorship hours (a) and the total implemented advice (b).

Figure 11 displays predicted outcomes based on the total number of implemented pieces of advice, grouped by the level of adjustment mentors made (low or high) to entrepreneur's plan. I measure the adjustment level for each entrepreneur using the average adjustment they received throughout the program. At each CDL session, mentors can alter one, two, or all three objectives initially proposed by an entrepreneur. Consequently, each session results in an adjustment level of 0, 1, 2, or 3 for each entrepreneur. The entrepreneur's adjustment level is defined as the average of these adjustments across sessions. The plot shows the predicted logarithm of funds raised by startups within one year after completing the Creative Destruction Lab (CDL) program, using Random Forest and Polynomial fits.

In figure 12, the left panel shows the relationship between the level of adjustment on advice and the total number of implemented pieces of advice, using Random Forest and Polynomial fits. The middle panel illustrates the predicted probability of graduation based on the total implemented advice, fitted using a Logit model. The right panel depicts the predicted probability of graduation based on the level of adjustment, also fitted using a Logit model.

To explore the effect of mentorship on final quality, I estimate the following model:

$$y_j = \beta_0 + \beta_1 Log(Mentorships) + \beta_2 Log(implementedObjectives) + Z_j + \epsilon_j \qquad (1)$$

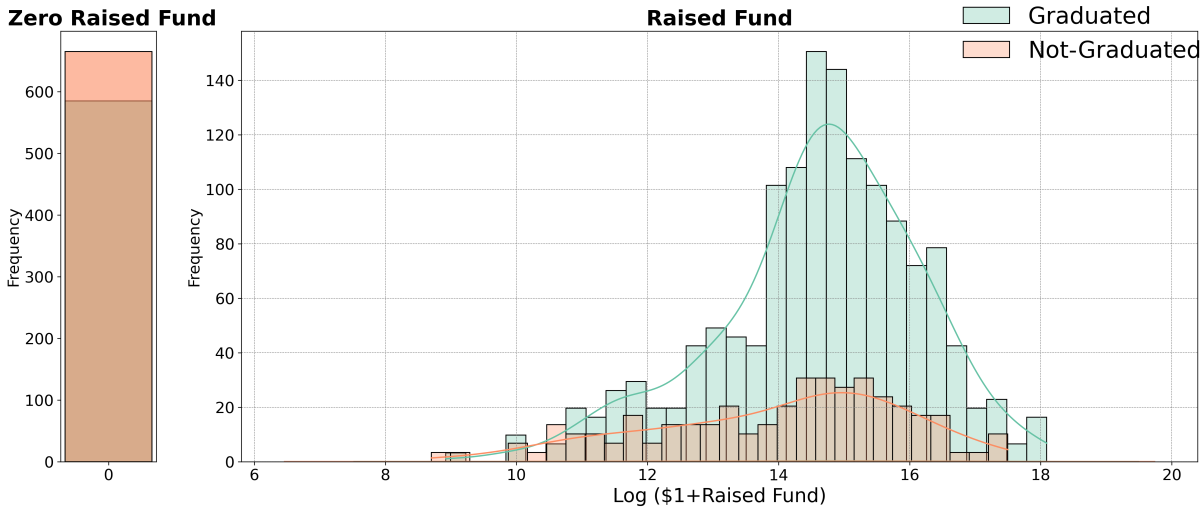


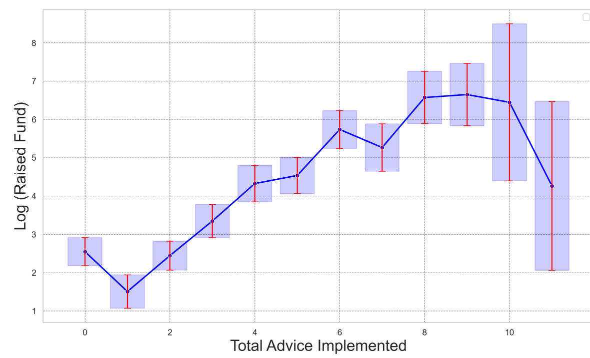
Figure 9: Distribution of the logarithm of raised funds after CDL, comparing startups that graduated from CDL and those that were cut from the program.

Where y_j is the final quality which I measure with the logarithm of raised fund within one year from CDL program. $Log(Mentorships)$ is the logarithm of total mentorship startup j received during CDL and $Log(implementedObjectives)$ is the logarithm of number of implemented objectives during CDL. I estimate this model to explore the effect of mentorship and implemented objectives on final quality. Since both mentorship and implemented objectives are endogenous, I use two exogenous shocks as instrumental variables. First instrument is the number of mentors that meet startup j during a SGM (Small Group Meeting) for the first time. Assignment to SGM is done by CDL organizer and is independent of startup potentials and quality. These SGM meetings changes mentoring decisions of mentors. The second instrument is a measure that shows whether startup j had absent existing mentors in a public session. The absence of an existing mentor due to personal schedules is independent of startup quality but changes the mentorship decision of other mentors.

Table 2 shows the result of the mentioned linear model. Column 1 shows the result of an OLS model. Both mentorship and implemented advice are positively correlated with the final quality. Columns 2-6 show the result of the same model using the mentioned instrumental variables. All results confirm a positive causal effect of mentorship and implemented objectives on the final quality. Column 7 shows the result of the same model where the dependent variable is Average Learning of Startup. I define learning as convergence of opinion between startup's proposed objectives and mentor's final objective at each session. This result suggests that through mentorship and achieving the objectives, startups learn how to prioritize their tasks and set objectives for their next steps.

I now present evidence on the effect of information shocks on mentorship choices. First I explore the effect of final quality which will be realized after CDL on mentorship decisions during CDL. I estimate a linear model where the dependent variable is the mentorship decision of mentors and the level of observations is mentor-startup-session.

(a) Mentorship Interactions and Performance



(b) Advice Implementation and Performance

Figure 10: Positive correlation between the logarithm of funds raised by startups within one year after participating in the Creative Destruction Lab (CDL) and (a) the total mentorship hours received and (b) the total number of implemented pieces of advice.

$$\text{MentorshipDecision}_{ijt} = \beta_0 + \beta_1(y_j \times x_{ijt}) + \beta_2 y_j + \beta_3 x_{ijt} + \epsilon_{ijt} \tag{2}$$

Table 3 presents the results of a linear model investigating the correlation between a startup's final quality and mentorship decisions. Column 1 shows that in session 1, the correlation between final quality and mentoring decisions is not statistically significant. However, in subsequent sessions, this correlation becomes positive and statistically significant, suggesting that over time, mentors might be learning about the potential quality of startups that is yet to be realized.

Column 3 reflects a similar trend, where the correlation between a startup's learning capacity and mentorship decisions grows stronger as sessions progress. Columns 2 and 4 show that engaging in mentorship interactions with a startup is correlated with mentorship decisions. These patterns suggest that mentors might be learning through their interactions, motivating the development of a learning model to better understand these dynamics.

I now investigate the correlation between two information shocks and mentoring decisions. The first is the assignment of a startup to a Small Group Meeting (SGM) by CDL organizers. During these sessions, the assigned mentors receive additional information about the startup, which might influences their decision-making in the subsequent public session where all mentors make their mentoring decisions. The second shock is for startups that have an existing mentor absent in the public session. When existing mentors are absent, there is a reduced amount of information available to other mentors in the room. This happens because mentors typically share their information about their mentee with all other mentors in the public meeting. Therefore, the absence of mentors can serve as a negative shock to the availability of information for that specific startup. I investigate the correlation between mentors subsequent mentorship decisions and these shocks by estimating the following linear models:

$$\text{MentorshipDecision}_{ijt} = \beta_0 + \beta_1(\text{Shock}_{ijt} \times x_{ijt}) + \beta_2 \text{Info Shock}_{ijt} + \beta_3 x_{ijt} + \epsilon_{ijt} \tag{3}$$

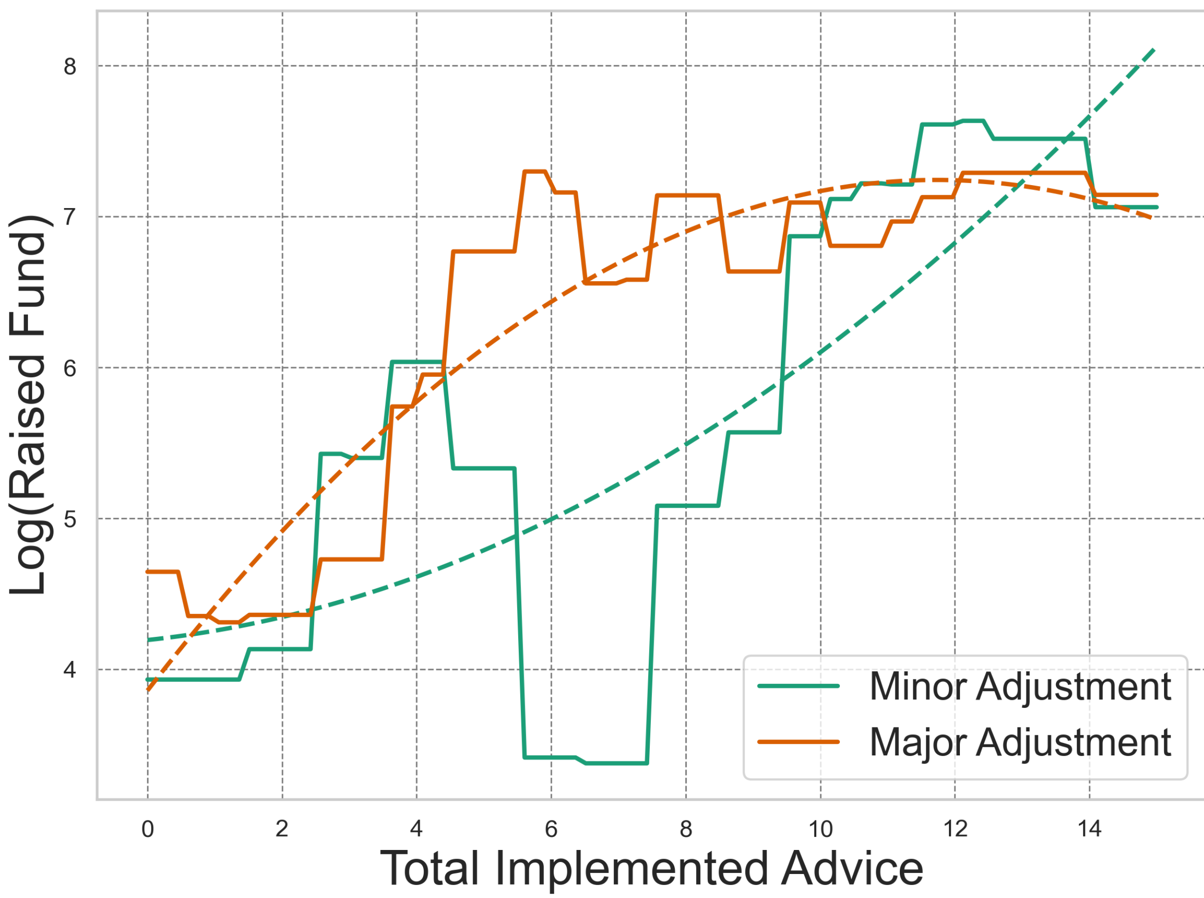


Figure 11: Predicted outcomes based on the total number of implemented pieces of advice, grouped by the level of adjustment mentors made (low or high) to entrepreneur's plan. The panel shows the predicted logarithm of funds raised within one year after attending CDL. The results are segmented into low, and high adjustment levels.

The results are presented in Table 4. Results show the correlation between mentorship decisions and information shocks. Column 1 shows a positive coefficient for the interaction term, suggesting that mentors without a prior mentorship history with a startup may be more likely to choose mentoring after a negative information shock (such as the absence of previous mentors), possibly indicating increased motivation to learn about the startup. Column 2 confirms this pattern using a stricter measure of no history, defined as not being an incumbent mentor. Columns 3 and 4 display similar patterns for Small Group Meeting (SGM) shocks, where negative coefficients for the interaction terms are consistent with decreased learning incentives following positive information shocks. Column 5 explores the heterogeneity of positive shocks in startups without competitors, showing that the positive coefficient of the triple interaction term suggests that even after a positive information shock, learning incentives might still be present for more innovative and uncertain startups, such as those claiming to be the first in their market.

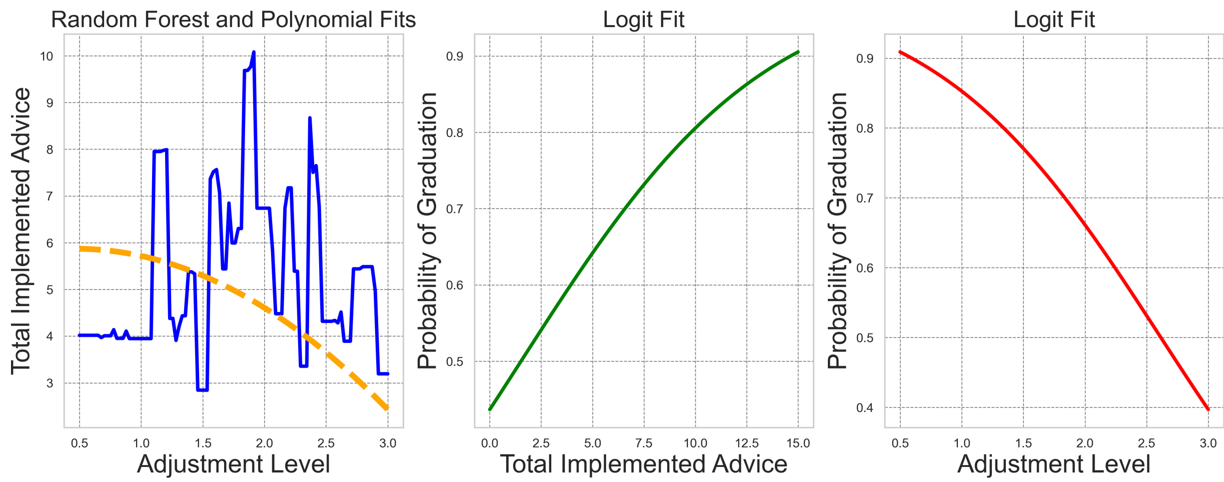


Figure 12: Relationships between adjustment level, implemented advice, and the predicted probability of startup graduation at the Creative Destruction Lab (CDL). The left panel shows the Random Forest and Polynomial fits for the predicted total implemented advice based on adjustment level. The middle and right panels display Logit fits for the predicted probability of graduation as functions of total implemented advice and adjustment level, respectively.

	Log(Post-CDL Raised Fund)			Log(Post-CDL Raised Fund)			Avg Learning of Venture
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	OLS	IV: Absent Mentor	IV: SGM	IV:Absent Mentor	IV: SGM	IV: Both	IV: Both
Log(Mentorship Votes)	2.417^{***}	2.410^{***}	3.378^{***}			1.836^{***}	0.186^{***}
	(0.219)	(0.425)	(0.526)			(0.659)	(0.0680)
Log(Achieved Objectives)	0.505^{*}			6.791^{***}	3.543^{***}	1.617^{*}	0.220^{**}
	(0.265)			(1.376)	(0.575)	(0.954)	(0.0985)
Log(Pre-CDL Capital)	0.133^{***}	0.133^{***}	0.126^{***}	0.146^{***}	0.148^{***}	0.136^{***}	-0.00229
	(0.0263)	(0.0264)	(0.0266)	(0.0301)	(0.0275)	(0.0267)	(0.00275)
Has Patent	0.288	0.293	0.306	0.192	0.224	0.269	-0.0691^{*}
	(0.362)	(0.362)	(0.364)	(0.416)	(0.379)	(0.364)	(0.0376)
No Competitor	-0.0561	-0.103	-0.0591	0.411	0.113	0.0196	-0.00521
	(0.368)	(0.368)	(0.370)	(0.441)	(0.388)	(0.375)	(0.0387)
Cohort_FE	Y	Y	Y	Y	Y	Y	Y
Site_FE	Y	Y	Y	Y	Y	Y	Y
Stream_FE	Y	Y	Y	Y	Y	Y	Y
Challenge_FE	Y	Y	Y	Y	Y	Y	Y
N	1794	1794	1794	1794	1794	1794	1794

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2: Results of the linear model assessing the impact of mentorship and implemented objectives on final startup quality. Column 1 presents the OLS model results, showing a positive correlation between mentorship, implemented objectives, and final quality. Columns 2-6 provide results using instrumental variables, confirming the positive causal effect of mentorship and implemented objectives on final quality. Column 7 reports the results with the dependent variable as the Average Learning of Startups, defined as the convergence of opinion between the startup's proposed objectives and the mentor's final objectives at each session. These results suggest that mentorship and achieving objectives help startups learn how to prioritize tasks and set objectives for future steps.

	(1) vote_mentorship	(2) vote_mentorship	(3) vote_mentorship	(4) vote_mentorship
session=2 × Log(Post-CDL Raised Fund)	0.000778***			
	(0.000176)			
session=3 × Log(Post-CDL Raised Fund)	0.00121***			
	(0.000221)			
session=4 × Log(Post-CDL Raised Fund)	0.00152***			
	(0.000289)			
session=5 × Log(Post-CDL Raised Fund)	0.00136***			
	(0.000358)			
History=1 × Log(Post-CDL Raised Fund)		0.00127		
		(0.000859)		
session=2 × Avg Learning of Venture			0.0131***	
			(0.00193)	
session=3 × Avg Learning of Venture			0.0261***	
			(0.00273)	
session=4 × Avg Learning of Venture			0.0364***	
			(0.00382)	
session=5 × Avg Learning of Venture			0.0270***	
			(0.00701)	
History=1 × Avg Learning of Venture				0.0337***
				(0.00989)
Log(Post-CDL Raised Fund)	0.00196	0.00425*		
	(0.00195)	(0.00230)		
Avg Learning of Venture			0.00320	0.0117**
			(0.00560)	(0.00510)
History=1		0.286***		0.292***
		(0.00819)		(0.00629)
session=2	-0.0132***		-0.00788***	
	(0.00152)		(0.00129)	
session=3	-0.0136***		-0.00600***	
	(0.00203)		(0.00162)	
session=4	-0.01000***		-0.00209	
	(0.00288)		(0.00222)	
session=5	-0.0612***		-0.0558***	
	(0.00380)		(0.00437)	
Cohort_FE	Y	Y	Y	Y
Site_FE	Y	Y	Y	Y
Stream_FE	Y	Y	Y	Y
Startup_FE	Y	Y	Y	Y
Mentor_FE	Y	Y	Y	Y
Challenge_FE	Y	Y	Y	Y
N	187980	135462	187980	135462

Standard errors in parentheses

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

Table 3: Results of a linear model investigating the correlation between a startup's final quality and mentorship decisions. Column 1 shows that in session 1, the correlation between final quality and mentorship decisions is not statistically significant. In subsequent sessions, this correlation becomes positive and statistically significant. Column 3 reflects a similar trend, with the correlation between a startup's quality and mentorship decisions strengthening over time. Columns 2 and 4 indicate that engaging in mentorship interactions with a startup is correlated with mentorship decisions.

	(1) vote_mentorship	(2) vote_mentorship	(3) vote_mentorship	(4) vote_mentorship	(5) vote_mentorship
Has Absent Mentor(Dummy)=1	-0.0758***	-0.0618***			
	(0.0103)	(0.0124)			
No History=1	-0.325***		-0.244***		-0.241***
	(0.00829)		(0.00737)		(0.00902)
Has Absent Mentor(Dummy)=1 × No History=1	0.0694***				
	(0.0106)				
Not Incumbent=1		-0.365***		-0.301***	
		(0.00922)		(0.00911)	
Has Absent Mentor(Dummy)=1 × Not Incumbent=1		0.0550***			
		(0.0126)			
SGM Meeting(Dummy)=1			0.165***	0.133***	0.178***
			(0.0104)	(0.0122)	(0.0129)
SGM Meeting(Dummy)=1 × No History=1			-0.0575***		-0.0758***
			(0.0107)		(0.0131)
SGM Meeting(Dummy)=1 × Not Incumbent=1				-0.0244**	
				(0.0124)	
No Competitor=1					0
					(.)
SGM Meeting(Dummy)=1 × No Competitor=1					-0.0423*
					(0.0216)
No History=1 × No Competitor=1					-0.0123
					(0.0153)
SGM Meeting(Dummy)=1 × No History=1 × No Competitor=1					0.0581***
					(0.0222)
Cohort_FE	Y	Y	Y	Y	Y
Site_FE	Y	Y	Y	Y	Y
Stream_FE	Y	Y	Y	Y	Y
Startup_FE	Y	Y	Y	Y	Y
Mentor_FE	Y	Y	Y	Y	Y
Challenge_FE	Y	Y	Y	Y	Y
N	135462	135462	135462	135462	135462

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results examining the correlation between mentorship decisions and information shocks. Column 1 shows a positive coefficient for the interaction term, indicating that mentors without a prior mentorship history with a startup are more likely to choose mentoring after a negative information shock. Column 2 presents a similar pattern using a stricter measure of no history, defined as not being an incumbent mentor. Columns 3 and 4 display negative coefficients for the interaction terms in the context of Small Group Meeting (SGM) shocks. Column 5 shows the results for startups without competitors, with a positive coefficient for the triple interaction term, suggesting a smaller reduction in mentorship following a positive information shock for these startups.

5 Structural Model

I develop a dynamic model of incomplete information where multiple mentors who are uncertain about the potential quality of the startups, make mentorship decision for startups across several session to allocate their time to them. Mentors' final session decision determines the graduation of a startup from the program. After the CDL, the true success of the startups realizes and true final quality reveals. Consider T periods $t \in \mathbf{T} = 1, 2, ..., T$ where T-1 sessions are mentorship sessions where mentors choose which startup to mentor and final session T they choose startups with the highest potential for future success. Mentors are indexed by i and startups are indexed by j .

5.1 Post-CDL Market

After the program, startups fail or enter the market and their true final quality reveals. Different factors including the mentorship received during the program and their characteristics affect their post-program performance. q_j^f is the final true quality of startup j which will be realized during the post-CDL market. I use logarithm of raised fund within 1 year after CDL as a measure of final quality or potential of success for each startup.

$$q_j^f = q_{j1} + \omega_1 \cdot A_j + \omega_2 \cdot D_j + \epsilon_j \tag{4}$$

where $D_j = \sum_i \sum_t d_{ijt}$ is the summation of all mentorship startup j has received during CDL. $d_{ijt} \in 0, 1$ is mentor i's mentorship decision about startup j at session t. q_{j1} is the true initial quality of startup j at the time of entering the CDL. ω_1 captures the effect of implementing advice on the final quality. ω_2 captures the effect of other mentorship benefits that are not captured in the advice implementation. $A_j = \sum_t a_{jt}$ is the total number of advice startup j has implemented during the program. At each session, startup receives three objectives from mentors to accomplish until next session. The effort and implementation skills of startup determines the number of implemented advice that directly changes the final quality.

ϵ: the unobservable term ϵ_j represents the random shocks or unobserved factors that affect the latent variable q_j^f and subsequently the final output Q_j^f. Specifically, ϵ_j captures the unobserved heterogeneity among different startups. These could be factors such as varying levels of effort, engagement, motivation, or external influences that are not directly measured in the model. Economically, ϵ_{jt} can be interpreted as representing the startups' effort in improving their projects, as well as other forces that contribute to changes in quality. These forces could include external factors such as market conditions, regulatory changes, or technological advancements that are not directly measured in the model. In the current version of the model, ϵ_j is considered an exogenous variable which is not influenced by the dynamic quality accumulation process itself. This assumption helps simplify the model and focus on the impact of the mentorship and implemented advice on quality accumulation. Endogeneity can arise if: $E(D_j \cdot \epsilon_j) \neq 0$

This correlation could bias the estimated parameters and lead to incorrect conclusions. To address potential endogeneity issues, I use Instrumental Variables to isolate the effects of mentorship and advice implementation.

5.2 CDL

This section explains the environment of the mentorship program in the model, specifying the roles of mentors and startups within a dynamic framework. I model the decision-making of mentors about which startups to mentor and in the last session of the program, which startup is worth to invest in. Mentors are agents in a dynamic incomplete information model. Mentors face uncertainty regarding the startups' final quality q_j^f and make sequential choices during the program about which startups to support. If all mentors decide not to choose a startup in session t, the startup is removed from the program, and the mentors lose the opportunity to explore it in the next sessions. For example, a mentor might choose to mentor a startup that no one else has chosen to improve their quality or to receive another signal of quality and learn about it.

Each mentor, has two major incentives to choose a startup. First, their ability to contribute to the startup's development and enhance its quality. The second incentive is the information mentors receive about the quality of the startup. Mentors have incentive to identify and graduate high-quality startups which can be investment opportunities in the future. To achieve this, mentors utilize two primary channels: their contributions to the startup's development and quality enhancement, and the information they receive about the startup's quality. These channels form the mentorship decision of mentors who choose which startup they want to interact with. As mentors contribute to a startup's quality growth, they also learn about the startup's potential.

5.2.1 Mentors' Decisions:

All mentors share a common prior belief about the initial quality of a startup, q_{j1}, denoted by μ_{j1}. After each session t, mentor i receives an unbiased signal about the true quality, which shapes her belief about the current quality of startup j. Mentor i's belief at session t is represented by μ_{ijt}. Consequently, mentors' updated beliefs over time are heterogeneous and depend on their previous interactions with the entrepreneur throughout the program. During the program, mentors decide at each session whether to mentor a particular startup based on their belief about the quality of that startup. d_{ijt} is the decision variable that indicates whether mentor i chooses startup j at time t. In this incomplete information model, the mentors are learning about an unknown parameter (the true initial quality of startups: q_{j1}). Mentors choose whether to choose a startup or not simultaneously and independently based on their updated beliefs.

Mentors make decisions based on their current knowledge. At period t, mentor i's utility from mentoring an available startup j or choosing the outside option is:

$$\begin{aligned} U_{ijt}(d_{ijt} = 1) &= \mu_{ijt} - c_{ijt} + \eta_{ijt_1} \\ U_{ijt}(d_{ijt} = 0) &= \eta_{ijt_0} \end{aligned} \tag{5}$$

Where c_{ijt} is mentors cost. Mentors maximize their utility at each period t based on their current beliefs and the cost of mentoring. Given that the preference shocks η_{ijt} and

η_{i0t} follow an extreme value type I distribution, the probability that mentor i chooses to mentor startup j at time t is given by the binary logit model:

$$p_{ijt} = P(d_{ijt} = 1) = \frac{\exp(\mu_{ijt} - c_{ijt})}{1 + \exp(\mu_{ijt} - c \cdot d_{ij(t-1)})}$$

At the final session T, mentors' decisions determine whether the startup should be graduated from the program and if it has the potential for success in the future. A startup that consistently receives at least one mentorship interest in all sessions, including the final session, graduates from the program. This final decision on whether a startup graduates is made in the last session T, where mentors choose based on their updated beliefs and the startup's progress.

Let g_j be the graduation status of startup j at the final session T, defined as:

$$g_j = \begin{cases} 1 & \text{if } \sum_i d_{ijT} \geq 1 \\ 0 & \text{otherwise} \end{cases}$$

Where $\sum_i d_{ijT} \geq 1$ indicates that at least one mentor has chosen to mentor startup j in the final session. The probability that startup j will be graduated from the program, conditional on the choices of the mentors in the final session, can be expressed as:

$$P(g_j = 1) = 1 - \prod_i (1 - p_{ijT})$$

Where p_{ijT} is the probability that mentor i chooses to mentor startup j at the final session T. This probability depends on the mentor's updated belief about the startup's quality and their assessment of its potential for success.

5.2.2 Entrepreneurs Implementation of Advice

In this section, I propose a binary choice model for advice implementation. Entrepreneurs receive advice in the form of objectives to accomplish, which can either align with their originally proposed objectives or be adjusted by mentors. Each piece of advice,r, is characterized by ($Objective, Adjustment$, where $Objective$ represents the type of task from the 10 categories of objectives, and $Adjustment$ is a binary variable indicating whether the objective has been adjusted by mentors or remains aligned with the entrepreneur's initial plan. The decision to implement or ignore this advice depends on the startups' perceived net benefit of implementation which depends on the potential quality improvement benefit of implementation, the level of adjustment to the objective, and the type of advice given. At each session, an entrepreneur receives three piece of advice than are ranked based on their priority. The decision to implement each piece of advice is made independently of other advice and is time independent. Let a_{jrt} be the indicator variable that takes the value 1 if entrepreneur j chooses to implement advice r, and 0 otherwise.

In this model, I do not explicitly model the objective-setting process and in the counterfactual analysis, I will evaluate an alternative objective setting process where mentors do not intervene in the entrepreneurs original plan and the counterfactual advice is then original objectives proposed by entrepreneurs without any intervention form mentors. entrepreneurs decision on proposing objective and mentors decision on whether to adjust these proposals is not explicitly modeled. By this simplification, the model focuses on the outcomes of advice implementation to capture the heterogeneity in the perceived net benefit of advice from entrepreneur's point of view based on the level of adjustment and type of objective. For example for easier types of objective, entrepreneur might see more benefit in implementing even if the plan has been adjusted by mentors, but for other types of objective they might choose to ignore the advice.

Let Agree_{jr} be a binary variable indicating whether the startup agrees with the objective ($\text{Agree}_{jr} = 1$ if they agree, 0 otherwise). The utility of entrepreneur j from implementing the advice $r = (Objective, Adjustment)$ is:

$$V_{jrt}(a_{jrt} = 1) = \omega_1 - IC(Objective, Adjustment) + \zeta_{jr_1t}$$

Where ω_1 is the quality improvement gain from implementing the advice and $IC(Objective, Adjustment)$ is the perceived implementation cost that depends on how difficult the task is and also on the adjustment. $IC(Objective, Adjustment)$ is indexed by both the type of objective and the level of adjustment. This means that each combination of objective type and adjustment level has its own specific implementation cost. The perceived implementation cost captures the difficulty and the alignment with the entrepreneur's perspective and drives the heterogeneity in the entrepreneurs advice adoption rate across different types of objective and different levels of adjustment.

Different types of objective (Sales and Marketing, Market Analysis, Business Planning, ...) have different levels of difficulty, resource requirements, and strategic importance. For example, implementing a complex product development task might be more costly in terms of time, effort, and resources compared to a marketing task. The level of adjustment to the direction of entrepreneur affects their willingness to implement and perceived cost of implementation.

5.2.3 Quality Improvement

The true quality is improved through a linear additive function and the effect of each mentorship on quality is ω_1.

$$q_{j(t+1)} = q_{jt} + \omega_1 \cdot \sum_r a_{jrt} + \omega_2 \cdot \sum_i d_{ijt} + \epsilon_{jt} \tag{6}$$

ϵ_{jt} represents startups effort in improving the project, as well as other forces that contribute to this change in quality. This variable is considered an exogenous and is not influenced by the dynamic quality accumulation process itself. Note that the exogenous ϵ in equation 4 is the summation of these shocks: $\epsilon_j = \sum_t \epsilon_{jt}$.

5.2.4 Mentors' Learning

All mentors share a common expected prior belief about quality of a startup q_{j1}: μ_{j1}. After any session t, mentor i receives an unbiased signal about the true quality and updates her belief. The rate of learning for mentors who have directly mentored startup is λ. Parameter $\gamma \in (0, 1)$, represents the degree of information sharing among mentors. In scenarios where a mentor does not directly mentor a startup, they can still learn about that startup through the shared knowledge from mentors who do.

A γ of 1 indicates full information sharing where all mentors learn at a same speed of λ. Lower values of γ lowers the rate of learning for mentors who do not directly interact with startup j. A γ of 0 represents an environment where learning is strictly a result of direct mentorship, with no benefits from shared information. Mentors update their beliefs based on their past mentorship choices, their priors, the rate of learning and the level of transparency and information disclosure in the program. Mentors receive unbiased signals about the initial true quality q_{j1}. They also fully observe the outcome of previous mentorships and progress in the program:

$$\mu_{ij}(t{+}1) = \begin{cases} \lambda \cdot q_{jt} + (1-\lambda) \cdot (\mu_{ijt} + \omega_1 \cdot \sum_r a_{jrt} + \omega_2 \cdot \sum_i d_{ijt}) & \text{if } d_{ijt} = 1 \\ \lambda \cdot \gamma \cdot q_{jt} + (1-\lambda \cdot \gamma) \cdot (\mu_{ijt} + \omega_1 \cdot \sum_r a_{jrt} + \omega_2 \cdot \sum_i d_{ijt}) & \text{if } d_{ijt} = 0 \text{ and } d_{i'jt} = 1 \end{cases} \tag{7}$$

In this model, mentors do not receive independent signals. If two mentors made the same voting decision for startup j at session 1, they have exactly the same belief at session 2. In this model, beliefs are solely updated through mentorship interactions, without any mentor-specific idiosyncratic elements. The updating process assumes that mentors rely entirely on their mentorship experiences and shared information from other mentors who have directly mentored the startup. This approach reflects a simplified learning mechanism where the primary drivers of belief updating are the direct mentorship activities and the degree of information sharing among mentors. This parametric learning model focuses on the impact of direct mentorship and shared information on the evolution of beliefs. This model assumes that mentors' beliefs are homogeneous among those who have taken similar actions, which helps in analyzing the collective impact of mentorship decisions on startup quality. The absence of mentor-specific idiosyncratic elements ensures that the belief updating process is consistent and predictable based on observable actions, which aligns with the objectives of this study.

5.3 Social Planner: Program Designer

The social planner maximizes the overall quality of the program. The welfare-maximizing equilibrium is the efficient allocation that optimizes both direct quality improvement of startups and the identification of high-quality startups by the final session. However, decentralized decision-making can lead to inefficiencies because mentors may have incomplete information about the quality of ideas, and there can be misalignment between the strategies proposed by entrepreneurs and the objective given by mentors. This misalignment affects the willingness to implement the advice.

The social planner optimizes both the direct quality improvement and the identification of high-quality startups. The social planner's problem is:

$$\max_{\{d_{ijt}^{SP}, a_{jrt}^{SP}\}} W(d_{ijt}^{SP}, a_{jt}^{SP} : \forall i, j, t) = \sum_i \sum_j g_j(d_{ijt}^{SP}, a_{jrt}^{SP}) \cdot q_{jT}(d_{ijt}^{SP}, a_{jt}^{SP}) \tag{8}$$

Where: d_{ijt} is the social planner's allocation. q_{jT} is the final quality of startup j and F is the fixed cost of the program. g_j is the graduation probability of startup j under the social planner's allocation

5.3.1 Welfare Gain

The gain from any counterfactual analysis is defined as the gap between the total utility implemented in the equilibrium resulting from the mentors' decentralized decision-making processes and the total utility in the social planner's welfare-maximizing equilibrium:

$$\text{Welfare Loss} = W(d_{ijt}^{SP}, a_{jrt}^{SP} : \forall i, j, t) - W(d_{ijt}^{*}, a_{jrt}^{*} : \forall i, j, t) \tag{9}$$

Where $(d_{ijt}^{*}, a_{jt}^{*})$ represents the equilibrium outcome of the mentors' decentralized decision-making and $(d_{ijt}^{SP}, a_{jt}^{SP})$ represents the efficient equilibrium outcome. This gain is decomposed to two components of quality gains and learning gains.

$$\begin{aligned} W^m - W^{cf} &= \sum_j g_j^m \cdot q_{jT}^m - \sum_j g_j^{cf} \cdot q_{jT}^{cf} \\ &= \sum_j q_{jT}^{cf} \cdot (g_j^m - g_j^{cf}) + \sum_j g_j^m \cdot (q_{jT}^m - q_{jT}^{cf}) \end{aligned} \tag{10}$$

6 Estimation and Identification Strategy

The goal of this section is to estimate the parameters of the structural model that describes the mentorship and quality accumulation process of startups. The model captures the dynamics of mentors' decision-making, the accumulation of startup quality over time and the evolution of mentors beliefs through learning. Suppose the cost of mentorship for all mentors is zero in the first session. However, there is an adjustment cost for subsequent sessions, meaning that mentors incur a cost if they switch to mentor a startup that they have not mentored in the previous session. This adjustment cost captures the persistency of mentors in their choices. Therefore, the cost of mentorship for mentor i for startup j at session t+1 is given by: $c_{ij(t+1)} = c \cdot (1 - d_{ijt})$

The main of parameters to estimate includes: ω_1: The effect of implemented advice on startup quality. ω_2: The effect of other mentorship benefits on startup quality. λ: The rate of learning from direct mentorship. γ: The degree of information sharing among mentors. μ_{j1}: The mentors' common prior beliefs about startup initial quality q_{j1}. IC: The perceived cost of implementation for each type of objective and level of adjustment. I use the mentorship data d_{ijt}, number of implemented advice by each startup at each session a_{jt} and final quality data q_j^f to estimate the structural parameters of the model.

6.1 Estimating the production function of quality

(Parameters ω_1,ω_2): To estimate the production function parameters ω_1 and ω_2, I estimate the model in equation 11. The main endogeneity problem in estimating the production function arises because q_{j1} (the initial quality of the startup) in equation 4 is not observable. Since q_{j1} is not included in the regression, it becomes part of the error term: $\nu_j = q_{j1} + \epsilon_j$. If q_{j1} is correlated with D_j and/or A_j, this correlation will bias the estimates of ω_1 and ω_2. Higher initial quality q_{j1} could lead to more mentorship allocation D_j and more advice implemented A_j, creating a reverse causality problem that further biases my estimates.

To mitigate these endogeneity issues, I use two instrumental variables (IV) that are correlated with the endogenous regressors D_j and A_j but uncorrelated with the error term $(q_{j1} + \epsilon_j)$. Even if I assume A_j (implementation effort of startups) is independent of q_{j1} (initial quality of the idea) and control for D_j (total mentorship), there can still be reasons for A_j to be endogenous. There might be unobserved factors that influence both the implementation effort (A_j) and the final quality (q_j^f). These could include factors like the startup's team dynamics, responsiveness, stubbornness or external support systems, which are not fully accounted for by D_j.

$$q_j^f = \alpha_0 + \omega_1 \cdot A_j + \omega_2 \cdot D_j + \nu_j \tag{11}$$

The first instrument is the number of mentors who have been assigned to a SGM (Small Group Meeting) as an instrument for total mentorship a startup receives. Before each public meeting, the program assigns each startup to multiple private meetings by different mentors. Through these assignments, startups meet with mentors, some of whom they have not previously met or engaged with. I use the number of such mentors (total number of first-time mentors through SGMs) as an instrument for the total mentorship a startup receives through CDL. The use of Small Group Meetings (SGMs) as an instrumental variable in the model is justified by their role as an exogenous shock to the information environment in which each mentor operates. SGMs increase the opportunities for mentors to interact with startups they have not previously met, thereby influencing the overall mentorship a startup receives (D_j). This additional interaction provides new information and insights about the startups, which in turn affects the likelihood of mentors deciding to mentor these startups. While SGMs are not explicitly included in the mentors decision-making model, they indirectly affect d_{ijt} by altering the external conditions and information available to mentors.

The exogeneity of SGMs is supported by the fact that their assignment is independent of the initial quality of the startups (q_{j1}) and other unobserved factors that influence the final quality (q_j^f). Therefore, SGMs provide valid and relevant exogenous variation in D_j without needing to be directly modeled in the d_{ijt} decision process. SGMs increase the opportunities for startups to interact with mentors, leading to enhanced guidance and resources, which directly affect the number of tasks a startup can accomplish (A_j). Thus, SGMs are relevant instruments as they influence A_j. SGMs are scheduled independently of the initial quality (q_{j1}) and other unobserved factors that could influence final quality. This ensures that the variation in A_j due to SGMs is exogenous.

The second instrument is the number of absent mentors in the current session who have chosen a startup in a previous session. Sariri Khayatzadeh (2021) uses the randomness in mentors schedule to identify the effect of mentorship on entrepreneur's learning. Since a mentor's personal reasons for skipping a session are not related to the startup quality, he constructs an instrumental variable based on the number of the startup's existing mentors who are present. I exploit the same exogenous variation to construct a second instrumental variable. The absence of mentors affects the total mentorship a startup receives and the distribution of mentorship efforts. This assumption holds because mentor absences are typically due to personal schedules, health issues, or other commitments unrelated to the startups' characteristics or performance.

The absence of previous mentors changes the pool of mentors available to each startup, thereby influencing the overall mentorship dynamics. Moreover, the absence of mentors who have previously chosen a startup affects the mentorship environment, reducing the available guidance and support, which directly impacts the startup's received advice and number of accomplish tasks (A_j). With fewer mentors available, startups receive less advice and fewer resources, which can hinder their task implementation efforts. Thus, the number of absent mentors serves as a relevant instrument for A_j as it introduces variation in the startup's ability to execute tasks effectively. Overall, the absence of mentors provides valid and relevant exogenous variation in both D_j and A_j.

By using these instruments, I isolate the exogenous component of the mentorship and task implementation processes to estimate the production function of quality in a first step of my estimation process. This first step simplifies the estimation of the structural model. I then use $\hat{\omega}_1$ and $\hat{\omega}_2$ to recover the initial qualities and estimate the rest of the structural model. Specifically, In a first step of estimating the model, I use the number of first-time mentors assigned to SGMs and the number of absent previous mentors as instruments in a two-stage least squares (2SLS) regression to obtain consistent estimates of the parameters ω_1 and ω_2.

Initial quality (q_{j1}): After estimating $\hat{\omega}_1$ and $\hat{\omega}_2$, I can recover the true initial quality $q_j 1$ and quality at subsequent sessions using the observed mentorship choices and implemented advice of each session. To do this, I make the following assumption: all quality-relevant shocks are captured through the variables D_j (mentorship effect) and A_j (startup implementation effort), meaning the residual term ϵ_j is zero. This assumption implies that the final quality (q_j^f) of a startup is determined by three main components: *Initial Quality (q_{j1})*: The inherent potential or starting quality of the startup. *Mentorship Effects (D_j)*: Contributions from mentors, such as connections, ideas, and strategic advice, that enhance the startup's quality. *Implementation Efforts (A_j)*: The startup's ability to effectively implement advice and strategies provided by mentors, reflecting their execution capability.

The assumption if that all shocks to quality improvement are effectively captured through D_j and A_j, meaning the observed variations in these components fully account for the changes in quality. The residual variation in the final quality after accounting for D_j and A_j is attributed to the initial quality (q_{j1}). Therefore, I can recover the initial quality (q_{j1}) using the following calculation:

$$q_{j1} = q_j^f - \hat{\omega}_1 \cdot A_j - \hat{\omega}_2 \cdot D_j$$

By isolating the exogenous variation in mentorship and task implementation, I ensure that the estimates of $\hat{\omega}_1$ and $\hat{\omega}_2$ are unbiased and consistent. These estimates provide a reliable foundation for the subsequent structural model estimation, allowing me to accurately capture the dynamics of mentors' decision-making, the accumulation of startup quality over time, and the evolution of mentors' beliefs through learning. This two-step approach allows me to decompose the complex estimation process into manageable parts.

6.2 Estimating the initial beliefs

Mentors' first session mentorship choice for a specific startup is based on their common prior belief about the quality of that startup. More specifically, the utility of mentor i from choosing startup j in the first session is given by:

$$\begin{aligned} u_{ij1}(d_{ij1} = 1) &= \mu_{j1} + \eta_{ij1_1} \\ u_{ij1}(d_{ij1} = 0) &= \eta_{ij1_0} \end{aligned} \tag{12}$$

where μ_{j1} represents the common prior belief about the quality of startup j, and η_{ij1_1} and η_{ij1_0} are idiosyncratic preference shocks for choosing startup j and the outside option.

I use the Hotz-Miller inversion method to estimate the fixed effects in this model and recover the common prior belief about each startup. The Hotz-Miller inversion method, introduced by Hotz and Miller (1993), is a technique used to estimate discrete choice models by using the relationship between the choice probabilities and the underlying utility parameters. The key insight of the method is that the choice probabilities, which are observed in the data, can be inverted to recover the utility parameters.

Given the observed choice data of mentor i choosing among startups in the first session, I calculate the empirical choice probabilities $p_{j1} = \frac{\sum_i d_{ij1}}{\sum_i 1}$, which represent the probability that a representative mentor chooses startup j in the first session. I recover the common initial beliefs about startups by inverting these choice probabilities as follows:

$$\mu_{j1} = \log\left(\frac{p_{j1}}{1 - p_{j1}}\right).$$

This formula comes from the logistic regression model, where the log-odds of choosing a startup are equal to the utility difference driven by μ_{j1}.

Finally, I define the initial bias for each startup as

$$\mathrm{b}_{j1} = q_{j1} - \mu_{j1}.$$

Larger values of bias indicate a lower valuation by mentors relative to the startup's true quality. This approach allows me to estimate the initial beliefs that mentors have about the startups.

6.3 Estimating the learning parameters

After recovering initial beliefs and initial qualities, learning parameters λ and γ can be identified through the effect of initial bias on subsequent mentorship decision of a mentors at next session. Based on the model, at session 2 mentors who have directly mentored a startup, receive a true signal of the initial quality (equivalent to a true signal of initial bias: $b_{j1} = q_{j1} - \mu_{j1}$. This signal affects their belief by rate of λ. Other mentors who have not mentored that startup, learn about that true quality with $\gamma \cdot \lambda$ rate where $\gamma \in (0, 1)$. Positive values of signal b_{j1} means the mentors have learned that the true quality is larger than their initial belief and negative values means they know they had previously overvalued that startup. More specifically, the utility of mentor i from choosing startup j in the second session is given by:

$$u_{ij2} = \mu_{j2} + \lambda d_{ij1} \cdot b_{j1} + \lambda \cdot \gamma(1 - d_{ij1}) \cdot b_{j1} + \eta_{ij2}$$

Note that mentors know the value of parameters $\hat{\omega}_1$ and $\hat{\omega}_2$ and observe previous session mentorships for each startup D_{j1} and their implemented advice A_{j1}. So, in the previous specification $\mu_{j2} = \mu_{j1} + \hat{\omega}_1 D_{j1} + \hat{\omega}_2 A_{j1}$. To jointly identify the learning parameters λ and γ, I use two types of variations in mentors' utility changes across sessions. First, the variation in utilities for a single mentor who has directly mentored two different startups identifies λ. Specifically, by comparing the utilities of the same mentor i for two startups j and j' in the second session, I can isolate the effect of the initial bias on the mentor's updated belief. Second, the variation in utilities for two mentors who made different choices regarding the same startup in the first session enables the identification of γ. By comparing the utilities of mentors i and i' for the same startup j in the second session, I can differentiate the learning rate for mentors who directly mentored the startup versus those who did not. These variations collectively provide the necessary information to jointly estimate λ and γ. Using Maximum Likelihood Estimation (MLE), I estimate these parameters to capture the learning dynamics in the mentorship model.

Identification of λ: The parameter λ can be identified by observing the variation in utilities when a mentor i has directly mentored startup j and has also mentored another startup j' in the first session. Specifically, consider the scenario where $d_{ij1} = 1$ and $d_{ij'1} = 1$. In the second session, the difference in utilities u_{ij2} and $u_{ij'2}$ provides the information needed to identify λ. The difference in utilities for mentor i between the two startups in the second session is:

$$u_{ij2} - u_{ij'2} = (\mu_{j2} - \mu_{j'2}) + \lambda(b_{j1} - b_{j'1}) + (\eta_{ij2} - \eta_{ij'2}).$$

By observing the variation in choice probabilities and also the differences in biases and initial beliefs, the parameter λ can be identified through the term $\lambda(b_{j1} - b_{j'1})$.

Identification of γ: Once λ is identified, γ can be identified by examining the variation in utilities for two mentors who made different choices regarding the same startup in the first session. Consider mentors i and i' with $d_{ij1} = 1$ and $d_{i'j1} = 0$. In the second session, the utilities u_{ij2} and $u_{i'j2}$ reflect different rates of learning based on direct and indirect mentorship interactions. The difference in utilities for mentors i and i' for startup j in the second session is:

$$u_{ij2} - u_{i'j2} = \lambda \cdot (1-\gamma)b_{j1} + (\eta_{ij2} - \eta_{i'j2}).$$

The parameter γ can be identified through the term $(\lambda - \gamma\lambda)b_{j1}$.

6.4 Estimating the perceived implementation costs

I generate the adjustment variable by comparing the category of objective proposed by the entrepreneur and the objective given by the mentor. Specifically, I use the Cohere API to categorize both the objective proposed by the entrepreneur and the objective given by the mentor into one of the 10 predefined categories. For each piece of objective, I compare the category proposed by the entrepreneur with the category of the mentor's objective and create a binary variable which takes the value 1 if the categories match and 0 if they do not match. The probability of implementing each piece of objective is estimated using a frequency estimator:

$$IC(Objective, Adjustment) = \hat{\omega_1} - \log\left(\frac{p_{(Objective,Adjustment)}}{1-p_{(Objective,Adjustment)}}\right)$$

Given the known parameter ω_1, the perceived implementation cost $IC(Objective, Adjustment)$ for each combination of category of objective and adjustment can be estimated using the logit model equation. This approach allows me to estimate the perceived implementation cost associated with each category of objective and level of adjustment based on the observed implementation frequencies in the data: $p_{(Objective,Adjustment)}$ probability of implementing advice $(Objective, Adjustment)$

7 Results

7.0.1 Production function of quality

Table 5 shows the results of estimating equation 11. The dependent variable is q_f, the final quality measure. The table presents the results of three models: OLS and two-stage least squares (2SLS) models. The 2SLS models use the number of first-time mentors assigned to Small Group Meetings (SGMs) and the number of absent previous mentors as instrumental variables for total mentorships and implemented advice. All models include fixed effects for cohort, site, stream, and the dominant challenge of startup.

One potential concern in estimating the production function parameters ω_1 and ω_2 arises due to sample selection bias in the first stage of the 2SLS estimation. Specifically, the removal of startups from the program in earlier sessions result in both the endogenous variable (mentorship allocations, D_j) and the instrument (SGM assignments) being zero for subsequent sessions. This truncation introduces a correlation between the instrument and the error term, thereby violating the exogeneity condition necessary for a valid instrument. This bias arises because the dropout of low-quality startups is not random but rather based on unobserved initial quality, creating a selection problem that biases the estimates of the production function parameters.

To address this sample selection bias, I employ a Heckman selection model (Heckman (1979)) for robustness check of my estimations: First, I model the probability of a startup remaining in the program using a probit model on observable factors that are likely correlated with the unobserved initial quality and determine the probability of remaining in the program. Second, I incorporate the Inverse Mills Ratio (IMR) derived from the selection equation into the production function estimation to correct for the selection bias. This two-step procedure ensures that the estimates of the production function parameters are robust to the sample selection bias introduced by the dropout of startups from the program.

Based on these estimations, implementing advice by startup improves the quality by $\hat{\omega_1} = 67\%$ and other benefits of a mentorship interaction increases the final quality by $\hat{\omega_2} = 25\%$ units. It is reasonable for startups to experience a large increase in their quality after receiving and implementing advice. Early-stage ventures operate with limited resources and often face high uncertainty, so even small adjustments in strategy or operations can lead to substantial improvements. This is because early-stage companies have more room to grow and can benefit significantly from each incremental improvement. Small changes, such as refining a business model, improving a product feature, or targeting the right market segment, can have large effects on their performance.

The inclusion of the Inverse Mills Ratio (IMR) in the 2SLS model shows the presence of sample selection bias, indicated by the negative coefficient of the IMR. Startups remaining in the program have unobserved characteristics negatively impacting their final performance. The estimates of the main parameters remain robust and significant after correcting for selection bias. This robustness suggests that the relationships between these variables and startup final quality are reliable and not substantially affected by the selection bias. The correlation between the Inverse Mills Ratio (IMR) and the survival of the startup in the program is negative (-0.2378). This negative correlation shows that startups with higher IMR values, which are less likely to survive, possess unobserved characteristics that negatively impact their final performance. This finding aligns with the significant negative coefficient of the IMR in the 2SLS model, confirming the presence of selection bias.

After estimating $\hat{\omega_1}$ and $\hat{\omega_2}$, I recover the initial quality and quality of startup at each session of CDL using the observed mentorship data: $q_{j1} = q_f - \hat{\omega_1} \cdot D_j - \hat{\omega_2} \cdot A_j$.

To further assess the validity of the instrumental variables (IVs) used in the model, I examine both their relevance and exogeneity. The following correlation matrix in table 7.0.1 provides some evidence. The reasonably strong correlations between the IVs and the endogenous variables (Mentorships D and implemented advice A) indicates that both IVs are relevant predictors of D and A.

While it is impossible to test the exclusion restriction directly because it involves unobservable factors, I provide indirect evidence to support instruments' validity. The IVs should not be correlated with the error term in the structural equation, which implies they should not be correlated with the unobserved determinants of the dependent variable (Initial Quality q_1). The correlation between Initial Quality and both IVs are very low that suggests the IVs are not correlated with the initial quality, supporting the exogeneity criterion. Furthermore, an OLS regression of Initial Quality q_1 on these IVs yields non-significant coefficients close to zero. This provides additional evidence that the IVs are not related to the unobserved determinants of the dependent variable. The F-statistics for the first-stage regressions in all 2SLS estimations are above 10, indicating that the instruments used are sufficiently strong.

	Final Quality				
	(1)	(2)	(3)	(4)	(5)
	OLS	2SLS	2SLS	2SLS	2SLS
Mentorship Interactions	0.415***	0.225**	0.253**	0.232**	0.260**
	(0.0387)	(0.109)	(0.106)	(0.109)	(0.106)
Implemented Objectives	0.193***	0.744***	0.673***	0.710***	0.658***
	(0.0640)	(0.246)	(0.246)	(0.252)	(0.245)
Has Patent			0.293		0.944**
			(0.373)		(0.473)
Has Prototype			-0.408		-3.887**
			(0.557)		(1.754)
No. of Founders			0.0227		0.283
			(0.143)		(0.190)
No. of Technologies			-0.0339		3.299**
			(0.453)		(1.579)
Log(Pre-CDL Capital)			0.145***		0.00159
			(0.0276)		(0.0738)
IMR				-4.992**	-23.14**
				(2.032)	(10.98)
Cohort_FE	Y	Y	Y	Y	Y
Site_FE	Y	Y	Y	Y	Y
Stream_FE	Y	Y	Y	Y	Y
Challenge_FE	Y	Y	Y	Y	Y
N	1794	1794	1782	1778	1778

Standard errors in parentheses

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

Table 5: Estimation results for production function of quality, with the dependent variable being q_f, the final quality measure. The table presents the results from three models: OLS and two-stage least squares (2SLS). The 2SLS models use the number of first-time mentors assigned to Small Group Meetings (SGMs) and the number of absent previous mentors as instrumental variables for total mentorship and implemented advice. All models include fixed effects for cohort, site, stream, and the startup's dominant challenge.

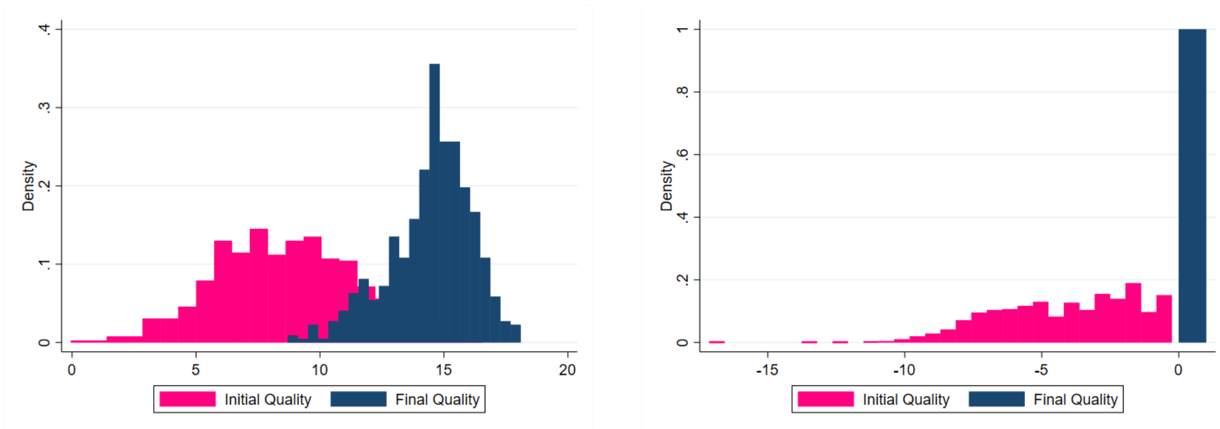
	Mentorship Interactions	Implemented Objectives	Final Quality
	(1)	(2)	(3)
	First Stage	First Stage	Second Stage
Mentorship Interactions			0.253**
			(0.106)
Implemented Objectives			0.673***
			(0.246)
Absent Previous Mentors	1.416***	0.268***	
	(0.0517)	(0.0365)	
SGM Assigned Mentors	0.147***	0.145***	
	(0.0122)	(0.00863)	
Has Patent	0.143	-0.0282	0.293
	(0.196)	(0.139)	(0.373)
Has Prototype	-0.541*	0.545***	-0.408
	(0.278)	(0.196)	(0.557)
No. of Founders	-0.0132	0.0121	0.0227
	(0.0757)	(0.0534)	(0.143)
No. of Technologies	0.152	-0.228	-0.0339
	(0.236)	(0.166)	(0.453)
Log(Pre-CDL Capital)	0.0303**	-0.0158	0.145***
	(0.0142)	(0.0100)	(0.0276)
Cohort_FE	Y	Y	Y
Site_FE	Y	Y	Y
Stream_FE	Y	Y	Y
Challenge_FE	Y	Y	Y
N	1782	1782	1782

Standard errors in parentheses

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

Table 6: First stage and second stage results.

I then back out the initial qualities by subtracting the effect of mentorship and effect of advice implementation from their final quality. Figure 13 shows the distribution of these initial qualities. The right figure shows startups with a final quality of zero, showing the distribution of their initial quality and the left figure shows the same distributions for startups who have raised money after the CDL program.



(a) Startups with positive final qualities

(b) Startups with final quality of 0

Figure 13: The distribution of initial qualities and final qualities

Table 7: Validity of Instruments

	C	
	Corr:Absent Mentors IV	Corr:SGM IV
Mentorships(D)	.5921337	.3947974
Accomplished Tasks(A)	.3436068	.478426
Initial Quality	.0286187	-.0137975

Table 8: Correlation matrix used to check the validity of the instrumental variables (IVs) in the model. The IVs show strong correlations with the endogenous variables and implemented advice, supporting the relevance condition. The low correlations with Initial Quality suggest that the IVs are likely not correlated with unobserved factors affecting the dependent variable, supporting the exclusion restriction.

7.0.2 Initial beliefs

I use the Hotz-Miller inversion method to recover common initial beliefs (equation 12):

$$\mu_{j1} = \log\left(\frac{p_{j1}}{1-p_{j1}}\right)$$

I define initial bias as the difference between initial quality and initial belief: $bias_{j1} = q_{j1} - \mu_{j1}$. Larger values of this variable indicate a greater undervaluation by mentors regarding the quality of the startup. Figure 14 shows three key distributions: True Initial Quality (q_1): Represented by the yellow bars. Common Initial Belief about q_1 (μ_1): Represented by the black bars.

The yellow distribution shows the true initial quality of the startups. The true initial quality values range widely, from around -15 to nearly 20. The distribution appears to be bimodal, with peaks around -10 and 10, suggesting that there are two distinct groups of

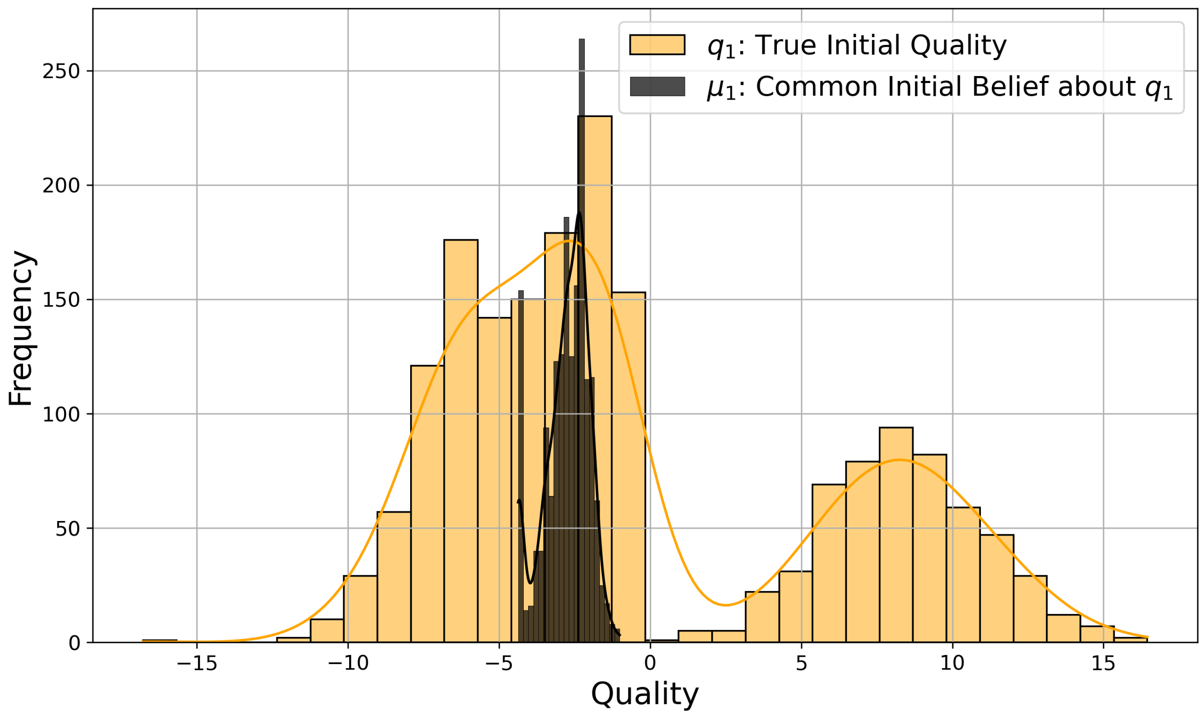


Figure 14: Distributions of: True Initial Quality shown by the hatched bars, Common Initial Belief about the Initial Quality represented by the solid bars, and Initial Bias the difference between the true quality and the common belief shown by the dotted bars.

startups in terms of initial quality. The bimodal nature of the true initial quality distribution indicates that the startups may have inherent heterogeneity, with distinct groups differing significantly in their initial quality levels.

The black distribution represents the common initial belief mentors have about the startups' initial quality. This distribution is much more concentrated around a narrower range, predominantly between -5 and 0. This indicates that mentors tend to have a more conservative and less varied initial assessment of the startups' quality compared to the true quality.

Mentors' common initial beliefs (μ_1) are much less dispersed compared to the true initial quality (q_1), showing that mentors tend to have a more conservative and clustered perception of startup quality. The significant variation in the initial bias highlights that mentors' initial beliefs often do not align with the true quality. This misalignment could lead to either undervaluation or overvaluation of startups, impacting subsequent mentorship decisions and startup outcomes.

7.0.3 Learning parameters

To estimate the rate of learning parameter (λ), the degree of information sharing (γ) and adjustment cost (c), I restrict my sample to mentorship choices in the second session of the program. Table 7.0.3 shows the estimation result of a conditional logit model using MLE.

Assuming that $\hat{\omega_1} = 0.67$ and $\hat{\omega_2} = 0.25$ from the first step, table 7.0.3 shows a learning rate of $\hat{\lambda} = 0.028 = 28\%$, a degree of information sharing of $\hat{\gamma} = 0.71 = 71\%$ and an adjustment cost of $\hat{c} = 2.5$. The low learning rate suggests that mentors are slow to update their beliefs about the initial quality of startups based on new private information that they receive through their interaction. While they fully observe and respond to measurable progress (such as the implementation of advice and other improvements during the mentorship process), their learning about the underlying, unobserved initial quality of the startup is slow. This finding is consistent with the concept of conservatism bias, where decision-makers tend to rely more heavily on their initial beliefs.

Table 9: Estimation Results with Bootstrap Standard Errors

Parameter	Estimate	Standard Error
λ	0.0279	0.0068
γ	0.7130	0.2268
c	2.5105	0.0158

I then calculate the evolution of belief and bias of each mentor about each startup over sessions using the estimated rate of learning, quality improvement parameter and initial beliefs:

$$
\begin{aligned}
b_{ij(t+1)} &= ((1-\hat{\lambda}) \cdot d_{ijt} + (1-\hat{\lambda} \cdot \hat{\gamma}) \cdot (1-d_{ijt}))b_{ijt} \\
\mu_{ij(t+1)} &= q_{j(t+1)} - b_{ij(t+1)}
\end{aligned}
$$

The slow learning rate can still be economically significant in this context because it measures how mentors update their beliefs about a startup's initial, unobserved quality—factors that are complex and not directly measurable. The information mentors learn comes from their private interactions with the startup they mentor. In my model, mentors fully respond to the implementation of objectives and the direct impacts of the mentorship process, consistent with the CDL structure where advice is centered around setting measurable objectives. The 2.8% learning rate specifically reflects how mentors update their beliefs about their initial biases.

An estimated $\gamma = 70\%$ shows a high level of information spillover among mentors. The specific feature of CDL where all mentors and startups meet in a large room and discuss the progress is consistent with my finding of the large information spillover from private mentorship interactions to other mentors. This substantial degree of information sharing suggests that mentorship interaction benefits others in the environment as it reveals information about the quality of startup.

7.0.4 Perceived Implementation costs

The results of the estimation for the perceived implementation costs of advice across different objective categories and adjustment are presented in Figure 15. This chart shows the estimated perceived costs of implementing advice across various categories and based on whether the mentor's advice was aligned with the entrepreneur's proposed objective or not. Each piece of advice is characterized by a task which is one of the categories of actions and a binary variable that determines whether this objective was adjusted by mentors or is aligned with the original proposal of entrepreneur. The estimated costs show that entrepreneurs respond to the mentors advice and adjustment. For example, entrepreneurs are more willing (and find it easier) to implement a mentor-driven marketing and sales plan that a marketing plan that was originally on their plan. This is intuitive since mentors likely bring an external perspective that helps identify areas where the startup has a readiness or comparative advantage, which the entrepreneur might not have fully recognized.

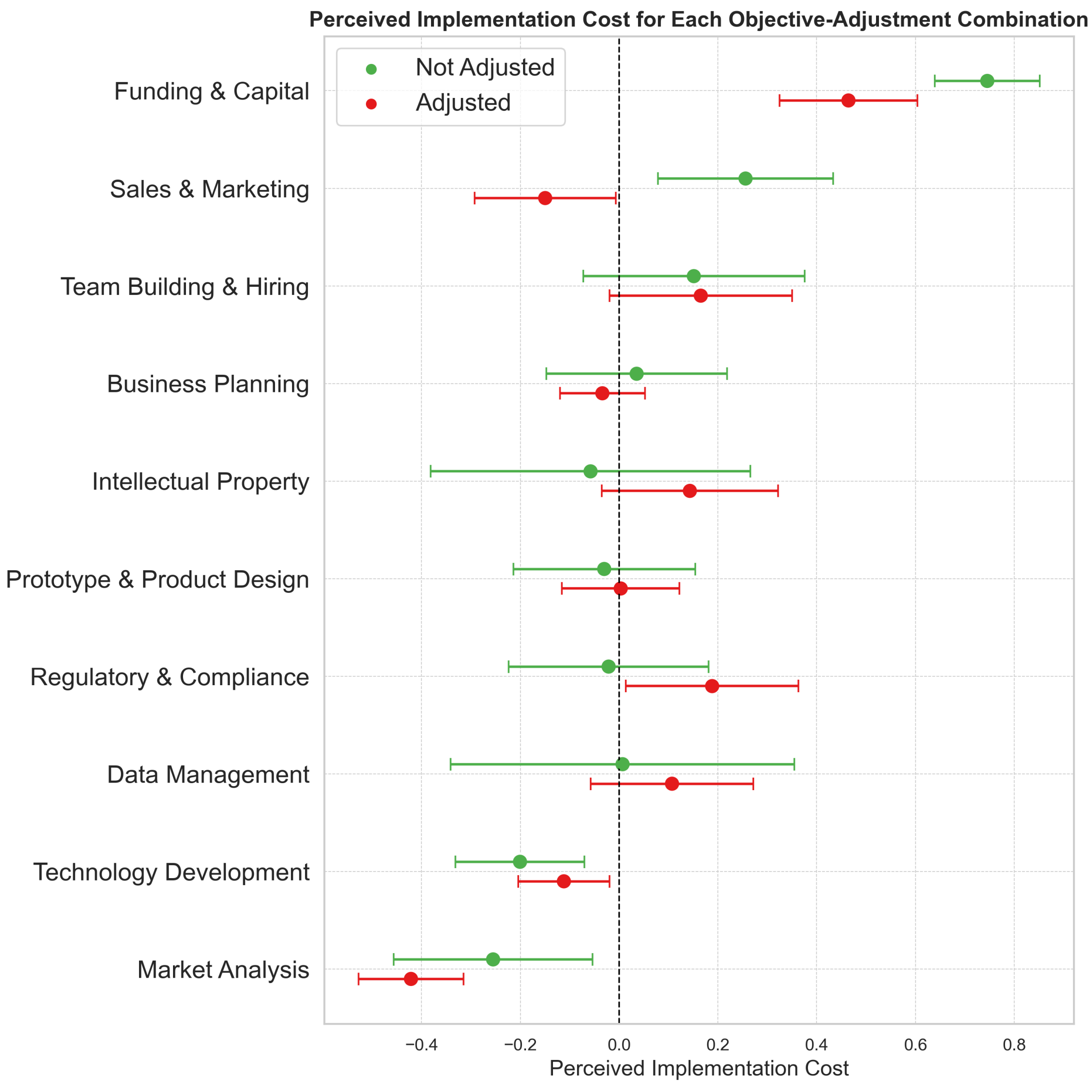


Figure 15: Estimated perceived implementation costs of advice across different categories and levels of adjustment. The costs are estimated based on the priority of the objective. The chart compares the implementation costs for advice aligned with the entrepreneur's proposed objective (Adjustment=0) versus objective that was not aligned (adjustment=0)

Negative effective costs in this model suggest that certain categories of objective are perceived by startups as beneficial in ways that go beyond the direct improvements in quality captured by parameter ω_1. This could be interpreted in a few ways: startups may find these tasks inherently rewarding or aligned with their competencies, increasing the willingness to implement them. Moreover, startups may already possess the skills and resources to implement these tasks efficiently. Furthermore, these tasks might offer benefits that are not directly captured by the model's parameters but are valuable to the startups, such as improving marketability or investor attractiveness in the long run.

7.1 Counterfactual Experiments

7.1.1 Trend of Welfare Gains

Now I explore the path of value created through sessions and decompose the path to focus on the path of learning gains. I estimate the value generated by each session by running simulations of removing each mentorship session from last session to the firs and compute the outcomes. First, by removing the last session, the graduates of the program are determined based on mentors updated beliefs up to session $T-1$, and one opportunity to improve quality is also missed. Mentors do not change their mentorship decisions as a result of one less available session. I measure the total welfare of the program by the total final quality of the graduated startups. Graduated startups are the startups who survive the mentorship sessions and receive a choice from at least one mentor during the final session. To explore the effect of removing one mentorship session from the program, I decompose the welfare loss into two main components: (1) missed learning opportunities and (2) missed quality improvements.

$$\begin{aligned} W^m - W^{cf} &= \sum_j g_j^m \cdot q_{jf}^m - \sum_j g_j^{cf} \cdot q_{jf}^{cf} \\ &= \sum_j q_{jf}^{cf} \cdot (g_j^m - g_j^{cf}) + \sum_j g_j^m (q_{jf}^m - q_{jf}^{cf}) \end{aligned} \tag{13}$$

Where W^m and W^{cf} are the total welfare of the program under the original model and counterfactual of removing the last session. g_j^m and g_j^{cf} are the probability of startup j being graduated from the program under the original and counterfactual models. q_{jf}^m and q_{jf}^{cf} are the final quality of startup j under both scenarios. The first component in the equation 13 is the negative of welfare loss due to the missed opportunity to learn and the second component is the negative welfare loss due to the foregone quality improvement. I define learning gain of additional session and quality gain of additional session for each startup as:

$$\begin{aligned} \textbf{Learning Gain}_j &= q_{jf}^{cf} \cdot (g_j^m - g_j^{cf}) \\ \textbf{Quality Gain}_j &= g_j^m (q_{jf}^m - q_{jf}^{cf}) \end{aligned} \tag{14}$$

Based on the estimated parameters of the model, initial qualities and beliefs, I calculate $\{g_j^m, g_j^{cf}, q_{jf}^m, q_{jf}^{cf}\}$ for each startup. The probability of startup j being graduated from the program is:

$$
\begin{aligned}
g_j^m &= 1 - \prod_i (1 - p_{ijT}^m) \\
g_j^{cf} &= 1 - \prod_i (1 - p_{ij(T-1)}^{cf})
\end{aligned}
\tag{15}
$$

where $p_{ijt} = \frac{\exp(\mu_{ijt})}{1+\exp(\mu_{ijt})}$. These probabilities depend on the mentors' beliefs about the startups μ_{ijt}. The learning gain of an additional session is realized by increasing the probability of graduating high-quality startups and decreasing the probability of graduating low-quality startups. The final qualities under two scenarios are:

$$
\begin{aligned}
q_{jf}^m &= q_{j1} + \hat{\omega_1} \sum_{t<=T} a_{jt}^m + \hat{\omega_2} \sum_{i,t<=T} p_{ijt}^m \\
q_{jf}^{cf} &= q_{j1} + \hat{\omega_1} \sum_{t<=T} a_{jt}^{cf} + \hat{\omega_2} \sum_{i,t<T} p_{ijt}^{cf}
\end{aligned}
\tag{16}
$$

Figure 16 illustrates the trend of welfare gains generated through multiple session of the CDL. The average Quality gains for a startup from the first session of the program is around 80% and diminishes over time. The average learning gain varies more by time. As a result of the mentorship process, mentors are able to identify startups that are, on average, 2.3% higher in quality than those they would have selected without that additional mentorship sessions. This 2.3% improvement reflects the mentors' improved ability to recognize and differentiate better-performing startups over time. Mentors identify startups with higher potential, which helps ensure that those chosen for graduation are the ones most likely to succeed. The learning gains result in more accurate selection, contributing to the overall success of the program.

Quality improvements are highest in the first session, possibly because early tasks and objective are easier to implement, making these initial gains less informative. As the program progresses and challenges increase, quality gains diminish. Initially, learning gains are on average negative but these gains grow as mentors better identify higher-quality startups.

Figure 17 shows the heterogeneity of decomposed gains across different sectors. Some sectors generate more value through resolving the uncertainty compared to other sectors. Figure **??** shows the path of learning gain for selected streams. In emerging markets where uncertainty is higher, the learning gains are very low and increase over time. In these sectors such as Quantum, mentors cannot distinguish between high and low quality in the early interactions. This is consistent with low learning rates about the true quality and ineffectiveness of early mentor-driven objectives in those sectors.

In line with Spence's signaling model (Spence (1973)), entrepreneurs implementation of mentor-driven objectives also serves as a signal about their quality. The informational value of the implementation outcomes comes from the fact that the mentor believes the implementation of these objectives is positively correlated with having higher quality. The screening gains then depends on the relevance and effectiveness of the objectives set by mentors. The heterogeneity in learning gain paths is consistent with a model where mentors in high uncertainty environments, initially offer less effective advice in a way that the implementation of those objectives is less correlated with the true quality of startups. However, as mentors observe cumulative signals over time, their uncertainty decreases, allowing them to set more precise objectives that better reflect the true quality of startups. This alignment improves the correlation between observable outcomes and actual startup quality, thus increasing learning gains over time.

This is consistent with Spence's model, where credentials serve as valuable signals only when they reliably correlate with higher quality and are costly to acquire by low quality ones. Implementing poorly aligned objectives can be particularly costly for high-quality entrepreneurs, as these paths are often irreversible. High-quality entrepreneurs are more likely to recognize when an objective is poorly suited, making it both costly and potentially damaging to implement such advice. In uncertain environments where mentor-driven objectives may be less relevant, signaling through these objectives could be especially costly for high-quality startups. Through more interactions, mentors accumulate information about the underlying quality of startups, enabling them to set more precise objectives that better reflect true quality. This leads to increasing screening gains in uncertain environments.

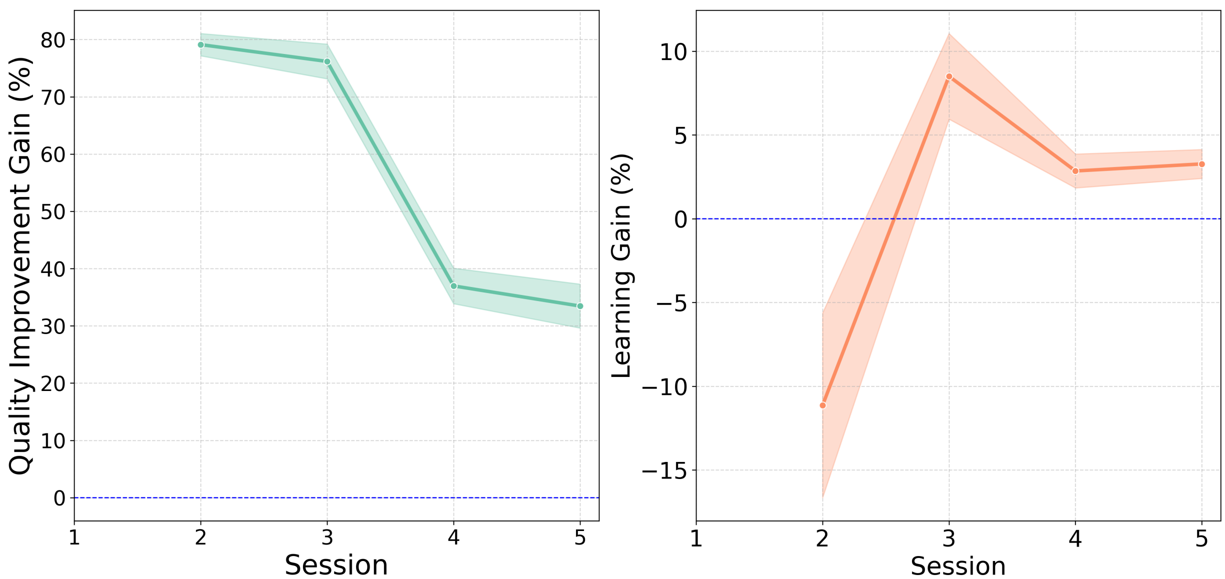


Figure 16: Trend of welfare gains generated through multiple sessions of the Creative Destruction Lab (CDL). The average quality gains for a startup from the first session are around 80% and decrease over time. The average learning gain shows more variation across sessions. Mentors identify startups that are, on average, 2.3% higher in quality after additional mentorship sessions compared to those selected without these sessions.

Figure 18 shows the path of learning gain for selected main objectives that are given to startups. Startups directed toward market analysis likely haven't yet confirmed product-market fit or fully understood their target market or when startups are advised to focus on technology development, it often means their core technology is still being validated or built. This stage is inherently uncertain due to technical feasibility concerns, the need for R&D, and unknown future scalability or application of the technology. Business Planning

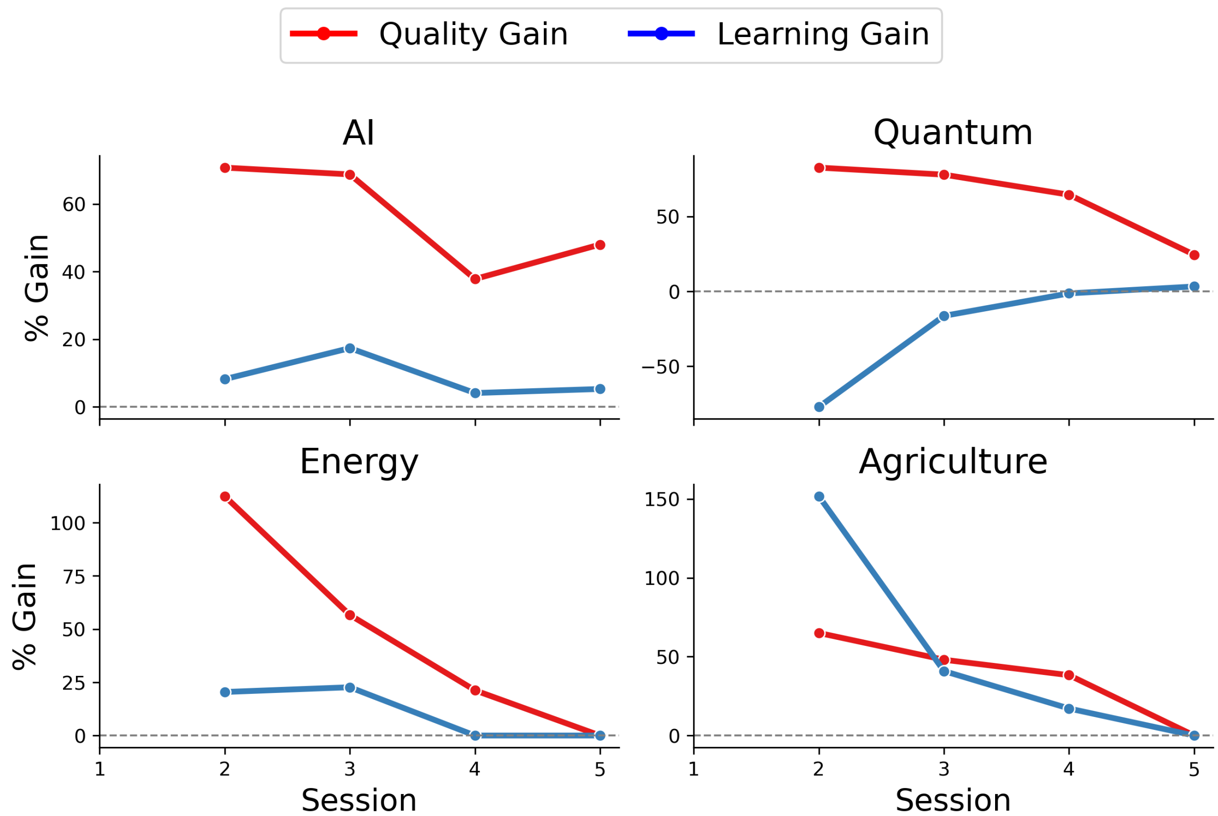


Figure 17: Heterogeneity of decomposed gains across some selected sectors.

and Funding and Capital objective assignments likely indicate a more mature stage with relatively clearer objectives and operational stability.

Figure 19 shows the path of learning gain for the stage of startup at time of application.

To see if the negative learning gains in emerging markets is leading to missing big ideas, I divide the entrepreneurs to top 30% and lower 70% based on their true quality. Figure 20 shows the trend of learning gain for these two groups of startups. Although the average learning for startups in Quantum sector is negative, the learning gains for the top quality ones is still positive.

7.2 Value of Mentors' Strategic Guidance

In this section, I conduct a counterfactual experiment that quantifies the value added by mentors when they play an active role in shaping the entrepreneurial strategy compared to when they play a more passive role and help entrepreneurs execute their own plan. Mentors help startups refine their strategies, which can improve the entrepreneurial choice. Entrepreneurs might suggest more ambitious and inherently costlier strategies, which may be harder to implement due to their complexity or resource requirements. This introduces a critical trade-off in evaluating the benefits of mentor-proposed strategy versus entrepreneur-proposed one. Mentors, based on their experience and external perspective, might focus

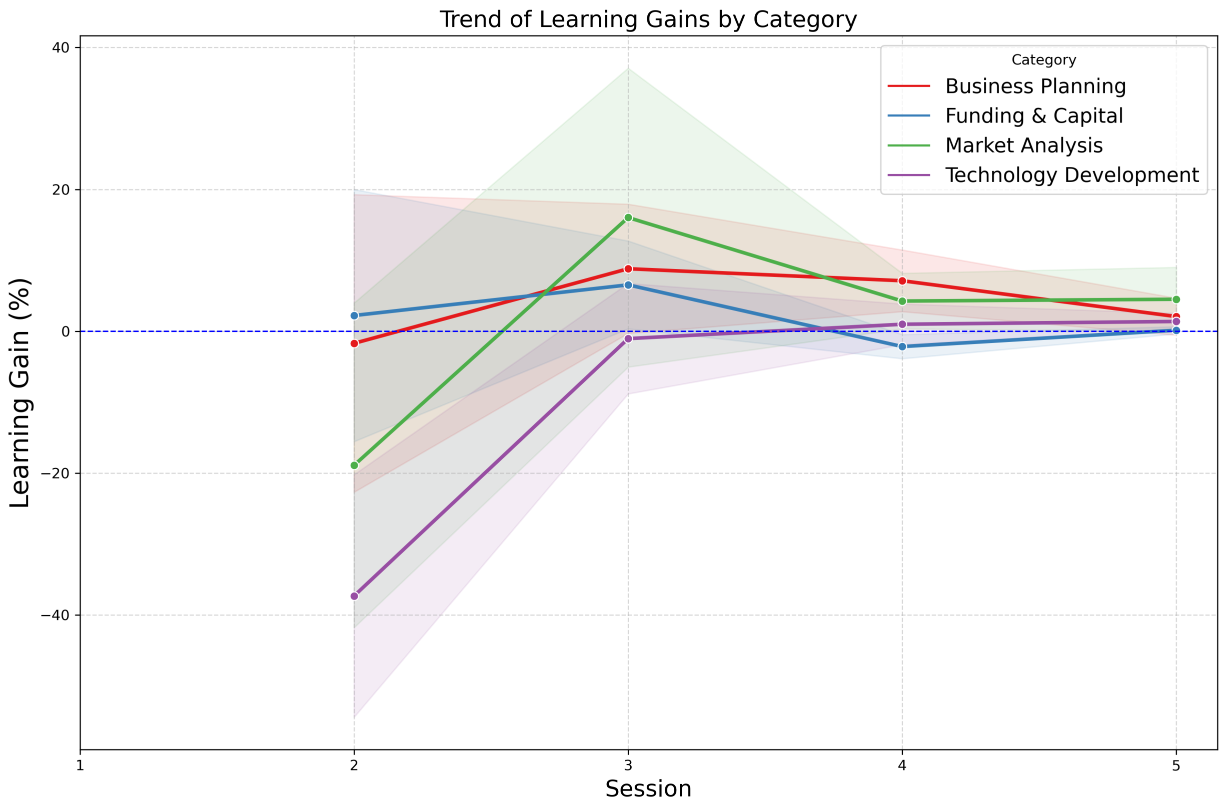


Figure 18: Trend of learning gains by the main objectives they receive.

on strategic changes that are essential for the startup's growth. However, mentors might have less understanding of the startup's comparative advantages and specific challenges, leading to advice that is not fully aligned with the startup's immediate capabilities. This simulation quantifies the value of mentors' intervention in driving strategic change.

I simulate a counterfactual of assigning the objective proposed by entrepreneurs as the final objectives and recalculating the perceived benefit and implementation rates under this scenario. Given the absence of a dynamic model for objective proposing, in this experiment I treat each session independently as if the next session was the final session (demo-day).

For each session, the objectives proposed by entrepreneurs are considered as the new objective. The perceived net benefit under the counterfactual scenario is recalculated by assigning the cost associated with the entrepreneur-proposed category under the adjustment condition. Using the recalculated perceived net benefits, I compute the counterfactual probability of implementation for each advice. To isolate the effect of change in objective, I fix the mentorship allocation as observed in the factual scenario. The underlying assumption is that mentors do not change their mentorship decision if the objective changes or the objective is proposed by entrepreneur. Next session is then treated as the final session where mentorship allocations define the graduation of the startups. The new objectives result in different implementation decisions which then result in different quality outcomes in the subsequent session and change the total gain.

Different implementation decisions also affects the relative weight of initial evaluation

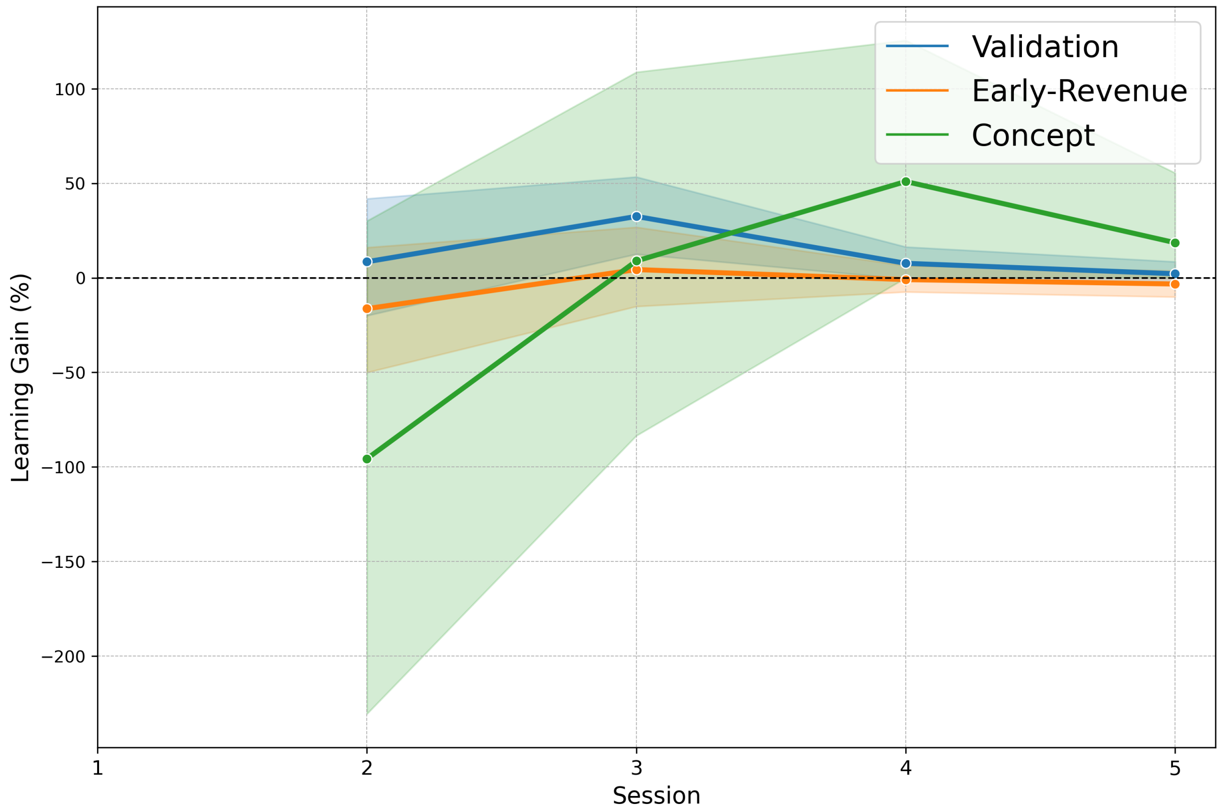


Figure 19: Trend of learning gains by the stage of startup at time of application.

of mentors in their subsequent mentorship decisions. It is intuitive since under more uncertainty or slow learning of mentors, advice implementation plays a more important role in helping the mentors to identify high quality ideas while under full information, the advice implementation only affects the level of quality improvement.

The experiment quantifies the additional value generated by mentors intervention in the strategic direction of startups. This gain can be decomposed to two main components as mentioned in the previous section: learning gains and quality gains. Figure 21 shows the scatter plot of the change in welfare resulting from the counterfactual experiment where the mentors only help with implementing the strategies proposed by the entrepreneur. Specifically shows the percentage of Quality Gain versus percentage of Learning Gain, colored by the percentage of Total Gain. In the actual scenario, mentors have the option to change the direction of an entrepreneur's strategy. The counterfactual scenario removes this option. Each dot on the graph represents a program-session. Positive values are the average value of mentors' strategic guidance for a whole program-session.

The color of the points represents the percentage of Total Gain (Welfare Change) from counterfactual scenario. Lighter color (Yellow) shows a positive welfare gain that represent the programs that benefit more from advice on entrepreneurs strategy. The plot shows that most of the program-sessions benefit from mentors intervention. The color gradient shows that these gains vary significantly across different programs.

Figure 22 shows the distribution of the gains. The first histogram shows the distribution

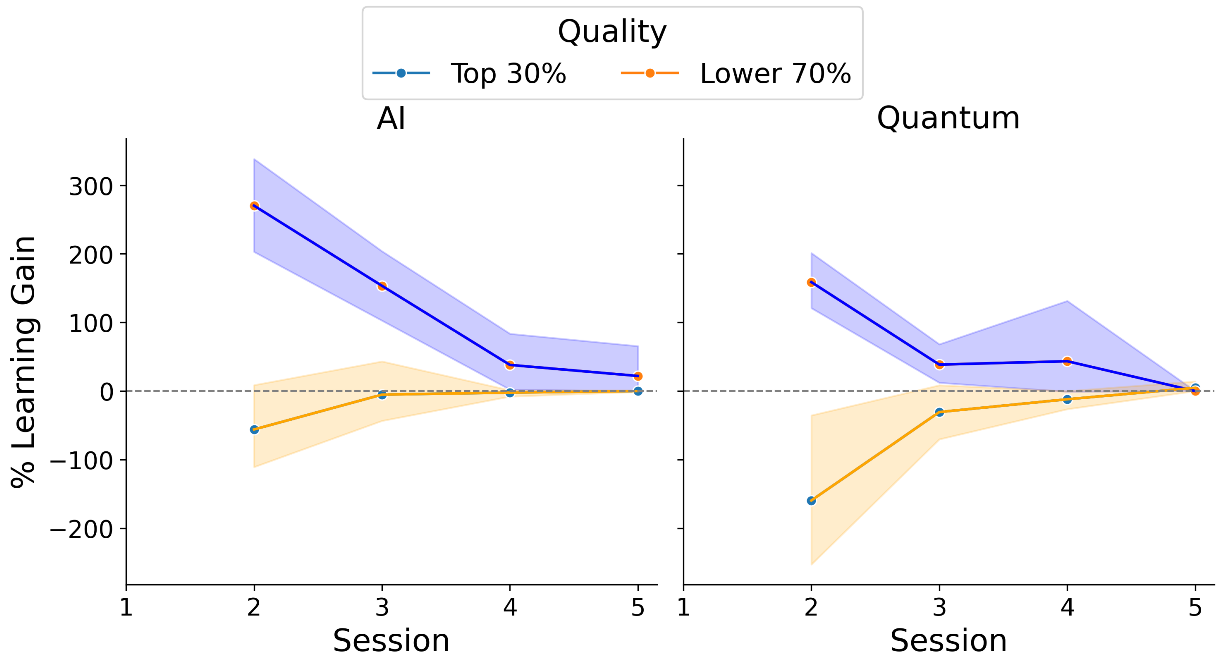


Figure 20: Path of learning gains for selected sectors.

of learning gains. This is the gain associated with mentors better identifying the high quality startups in the final session. Since the intervention changes the entrepreneur's implementation choice, it also influences the observed quality improvements by the mentors. This, in turn, changes the relative weight mentors place on their initial evaluations, which may be inaccurate, when making their final session decisions to identify high quality ideas. The second histogram shows the gain associated with the change in implementation rate which translates into changes in quality improvements.

Figure 23 shows the average value of mentors' strategic guidance across different streams. The variation in welfare gains across different streams suggests that the effectiveness of mentor-driven strategy changes varies by industry or sector. Streams with higher total welfare gains, such as Fintech and Recovery, show that startups in these areas benefit more from strategic guidance provided by mentors. This implies that the potential for mentorship to add value is greater in certain industries, possibly due to differences in uncertainties associated with those markets, market dynamics, the complexity of challenges faced, or the specific nature of entrepreneurial activities in those areas. The variation in gains across different streams suggests that some sectors may benefit more from strategic interventions than others.

Figure 24 shows the average welfare gains based on the stage of startups at the time of application and Figure 25 shows the average welfare gains based on the main objective startups receive.

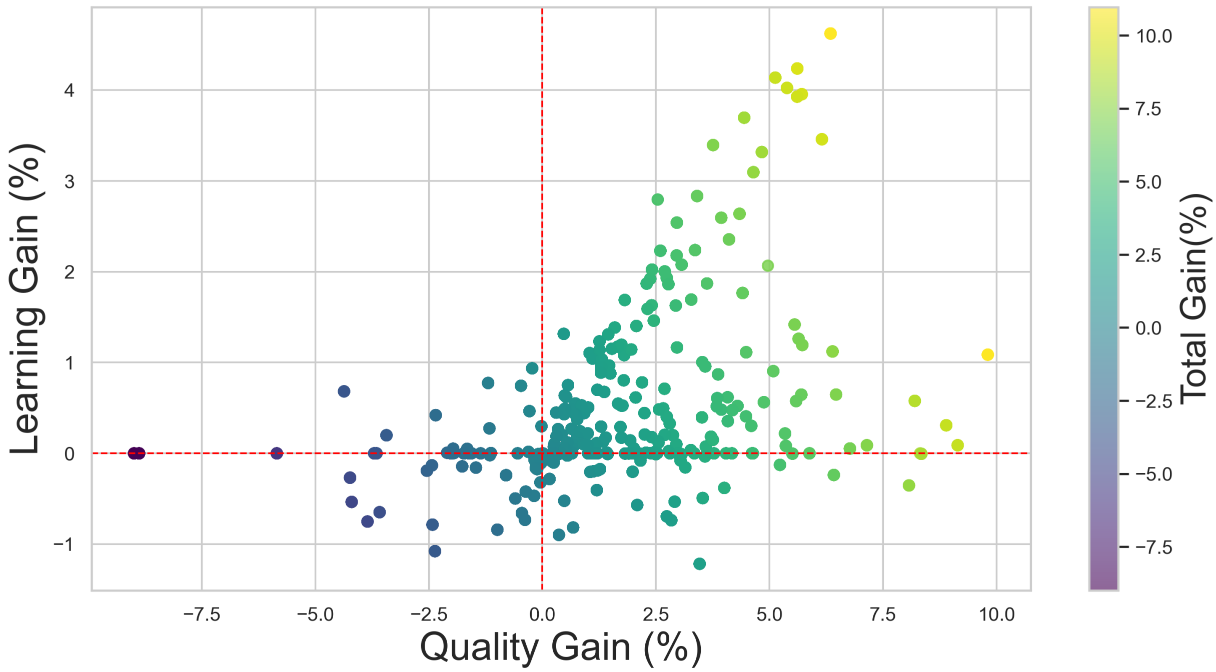


Figure 21: The percentage of Quality Gain versus percentage of Learning Gain, colored by the percentage of Total Gain. Each dot on the graph represents a program-session. Positive values are the average welfare gained for a whole program-session by allowing mentors to give advice on the entrepreneur's strategy, compared to helping with the proposed strategies. The plot shows that most of the program-sessions benefit from mentors' intervention. The color gradient shows that these gains vary significantly across different programs.

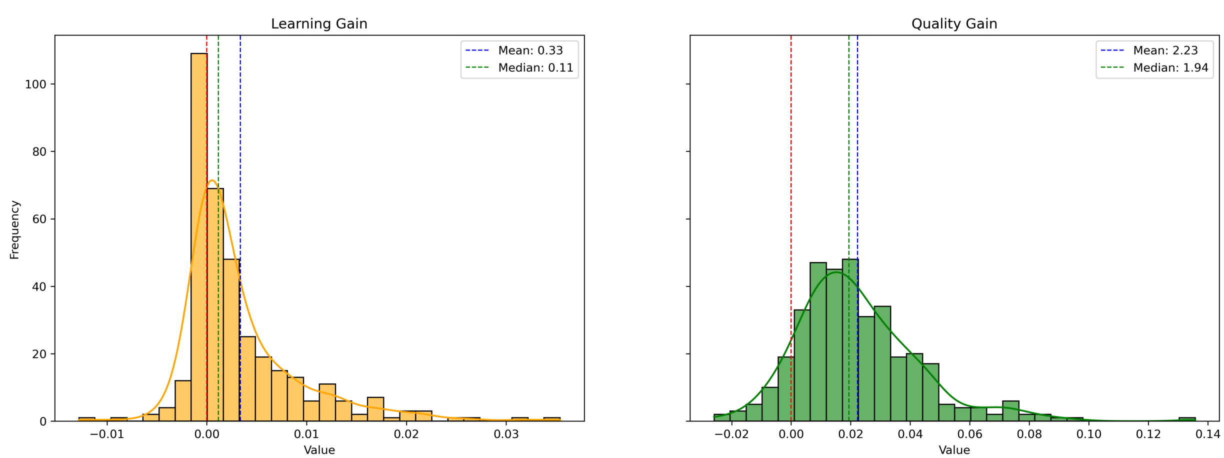


Figure 22: The distribution of the gains from mentors' strategic guidance. This is the gain associated with mentors better identifying the high quality startups in the final session. The second histogram shows the gain associated with the change in implementation rate which translates into changes in quality improvements.

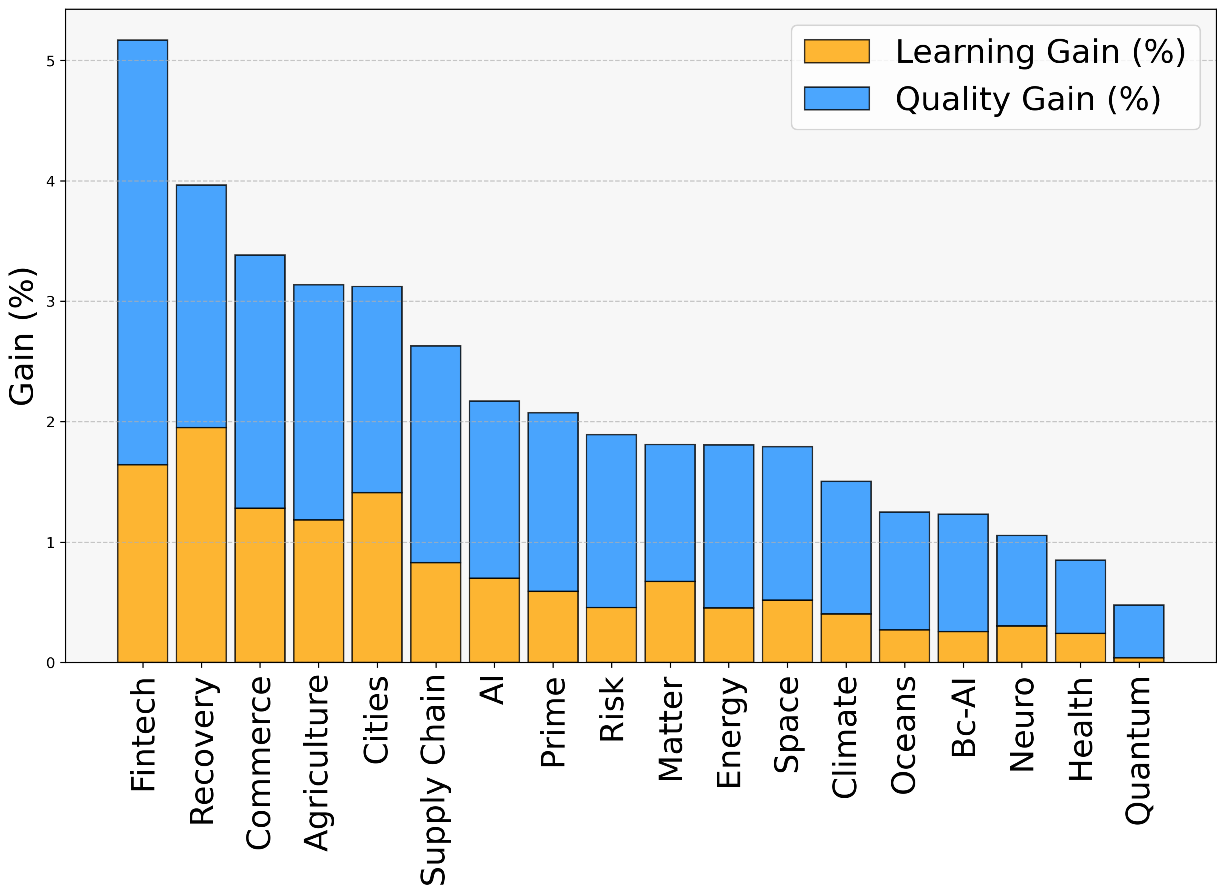


Figure 23: The average welfare gains across different streams.

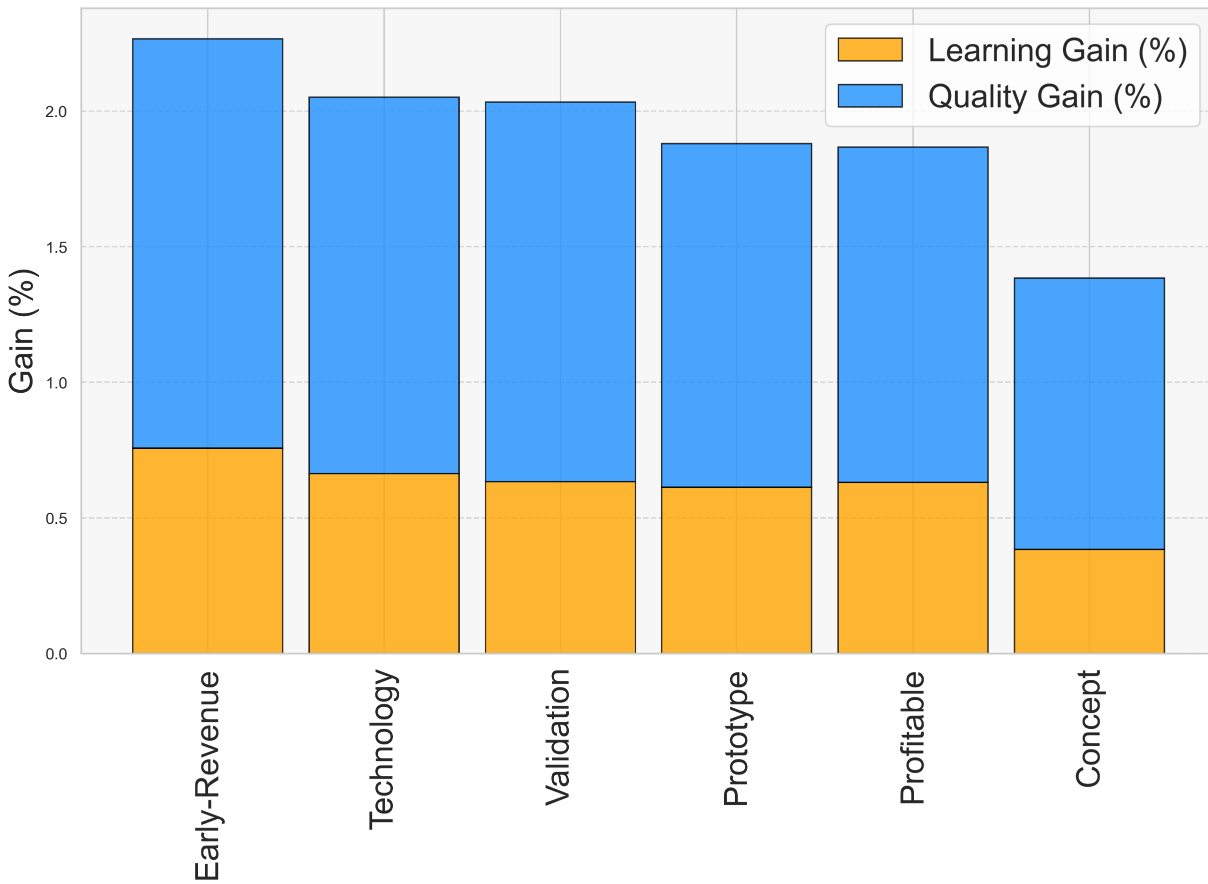


Figure 24: The average welfare gains based on the stage of startups at the time of application.

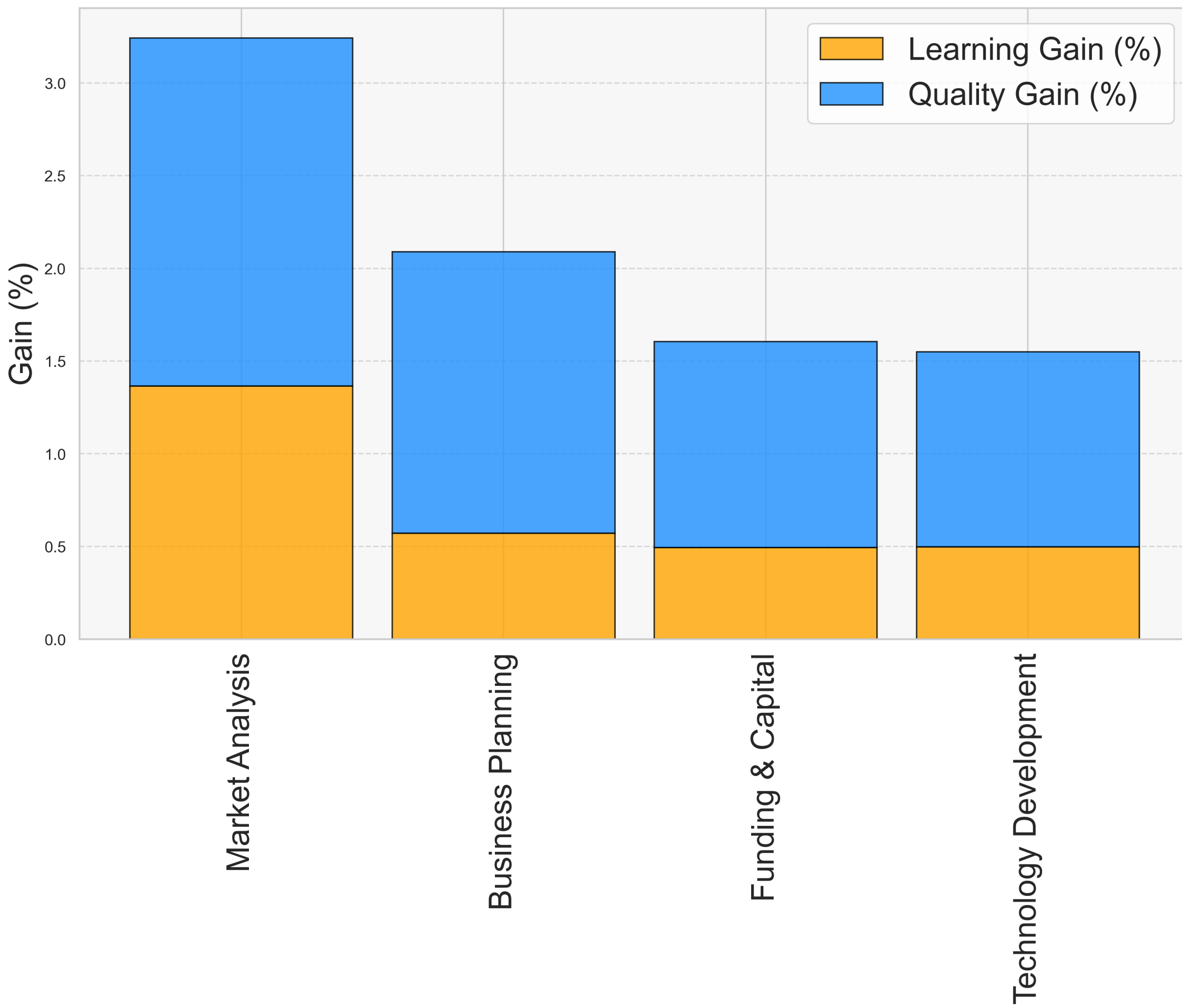


Figure 25: The average welfare gains based on the main objective startups receive.

8 Conclusion

In this paper,I explored the mechanisms through which mentorship improves entrepreneurial success within the context of the Creative Destruction Lab (CDL), a global mentorship-driven startup accelerator. By estimating a dynamic structural model of incomplete information, I separated and quantified the value of mentorship in both reducing uncertainty around the quality of startup ideas and directly enhancing startup performance through the implementation of advice. The findings show that mentorship interactions lead to significant improvements in startup quality, with mentors' learning playing a crucial role in the early identification of high-potential startups.

I find that mentors learn about the underlying quality of startups from their private interaction with entrepreneurs. The rate of learning about the underlying unobservable quality is slow, but the spillover of this learning on other mentors in the program is high. The slow learning learn implies that most of the mentors decision and evaluation rely on the observable progress and outcome of the objective implementations in the program. So, the objective setting process and the effectiveness of those objectives play an important role in this setting. The gains from this screening channel are heterogeneous across different sectors. For startups in more traditional sectors such as energy or agriculture, most of the mentors learning happen in the early sessions and diminish over time, but for startups in emerging sectors such as Quantum, the learning gains are lower in the early sessions and increase over sessions.

I find that entrepreneurs respond to mentor-driven strategies. This finding shows that the intervention of mentors can significantly influence entrepreneurial decisions and strategic direction, leading to better outcomes for startups. The counterfactual analysis investigates the value of advice in guiding entrepreneurs to set and prioritize tasks. The findings reveal the critical role of mentorship in shaping the strategic decisions that drive entrepreneurial success. I find a significant heterogeneity in the benefits from mentors strategic guidance among startups in different sectors. In uncertain environments where quality is hard to observe, passive mentorship approach is more effective

My work provides actionable implications for both entrepreneurs and mentorship-driven programs. For entrepreneurs, understanding how and when to incorporate mentor advice can help them make more informed decisions, particularly when facing uncertainty or entering new markets. For mentorship programs, these findings suggest that a one-size-fits-all approach may be less effective. Instead, programs should consider targeted mentorship strategies to fit the unique characteristics of each sector, ensuring that the advice given is relevant and effective.

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