A structural model of mentorship in startup accelerators: Matching, learning, and value creation (JMP: *Click here for the latest version*.)

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Abstract

Entrepreneurial success depends on reducing uncertainty about the quality of ideas and selecting the best strategies to implement. Mentorship plays a crucial role in this process. This paper examines how mentorship improves entrepreneurial success within the Creative Destruction Lab (CDL), a global mentorship-driven startup accelerator. I investigate two key channels. First, I examine how mentors' learning about the startup potential influences mentors' allocation of mentorship resources. Second, I examine how mentor advice shapes entrepreneur decisions, potentially leading to better outcomes. I use mentorship interaction data from CDL, complemented with Crunchbase. I identify the types of decisions using generative AI techniques for text analysis. I use this data to estimate a dynamic structural model of incomplete information. This model captures the dynamics of mentor learning, advice implementation, and quality accumulation, enabling me to separate and quantify the value of mentorship in resolving the uncertainty around the quality of the idea and directly improving the quality itself. I use this model to conduct counterfactual analysis, simulating the effects of a policy where entrepreneurs are supported in pursuing their original plans, rather than receiving mentor-driven suggestions for alternative strategies. I estimate that the advice given by mentors is more likely to be completed, and that it is more likely to lead to successful outcomes for the startup overall, than the entrepreneur's initial plan. I also demonstrate substantial spillovers of private quality signals between mentors. Overall, I document the mentors provide substantial value in both identifying the higher quality startups and providing those startups with strategic direction.

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1 Introduction

Entrepreneurship is a key driver of economic growth, increasing innovation, creating jobs, and boosting productivity. To commercialize their ideas, entrepreneurs must choose between multiple potential strategies, and their success depends on both the quality of the idea 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 process involves designing experiments or tests to assess the quality of their ideas and the effectiveness of multiple strategies. Sevilla-Bernardo et al. (2022) provides a comprehensive review of the entrepreneurial literature and identifies several key factors and practical business elements that contribute to the success of startups. The first most important factor is the idea that delivers real value and the second factor is the founder strategic decision-making.

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)).

This paper explores the mechanisms through which mentorship improves entrepreneurial performance within a mentorship-driven accelerator program, Creative Destruction Lab (CDL). Specifically, it investigates two key channels. First, mentors' learning channel 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. The second channel, advice on entrepreneurial decisions, examines how mentor advice shapes entrepreneur decisions, potentially leading to better outcomes. Entrepreneurs may set ambitious and costly plans, prioritizing tasks that can be challenging to implement, or they might choose more beneficial goals if they have a deeper understanding of their idea. Mentors, leveraging their experience and external perspective, can suggest an alternative plan that provide more informative signals about the quality of the idea or the effectiveness of different strategies.

Addressing the research questions in this study is challenging due to several key is-

[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)).

sues, particularly in identifying the impact of mentorship, measuring the advice on entrepreneurial decisions, and establishing relevant counterfactual analysis. 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.

Mentorship is also subject to selection bias. The other common challenge is that 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 have 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.

Another 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. However, 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.

The unique feature of the Creative Destruction Lab (CDL), where entrepreneurs propose initial plans and mentors suggest alternatives, 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 mentor selection, the learning process of mentors, and the endogenous decisions of entrepreneurs to implement the advice they receive. To capture the mentor's learning channel, 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' after CDL performance. I measure the final quality (performance) of startup by logarithm of the raised fund within one year after the CDL attendance.

In the mentors' learning channel, I find that through mentorship interactions and by observing quality improvements, mentors learn about the startups' potential and can identify higher-quality startups 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. To capture the dynamics of learning gains across multiple sessions, I conduct a counterfactual analysis by sequentially omitting each session from the CDL program and evaluating the specific gains attributed to that 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.

The estimates from my learning model reveal that mentors' initial beliefs about a startup's final performance are conservative, avoiding extreme evaluations and generally undervaluing startups. Mentors update their beliefs about the startup's initial unobserved quality at a slow rate, while information spillover among mentors is substantial. This suggests that much of the mentors' learning occurs through observing the quality improvements that result from advice implementation and mentorship allocations. These findings highlight the importance of establishing measurable and observable objectives to accurately assess the potential of an entrepreneurial idea.

In the advice on entrepreneurial choice channel, 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 choice 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 that mentorship alone may not sufficiently provide.

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)).

2 Creative Destruction Lab (CDL)

2.1 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.

2.2 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.

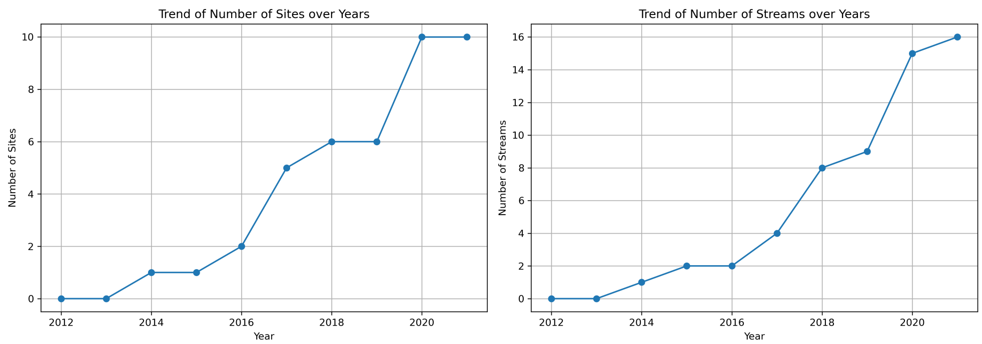


Figure 1: The trend in the number of sites and streams at the Creative Destruction Lab.

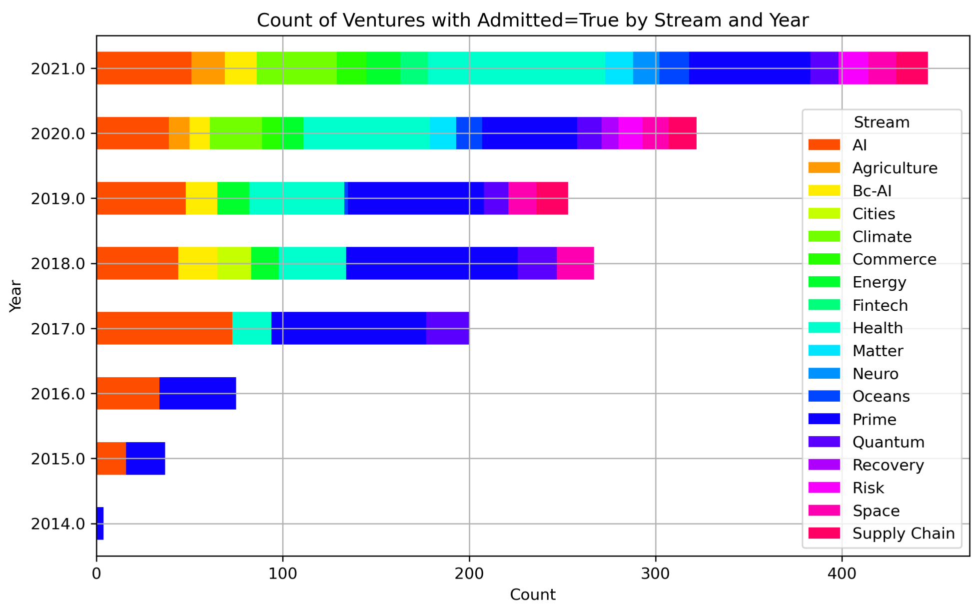


Figure 2: Introduction of new streams at the Creative Destruction Lab over the years and the distribution of accepted startups across each stream.

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.

2.3 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

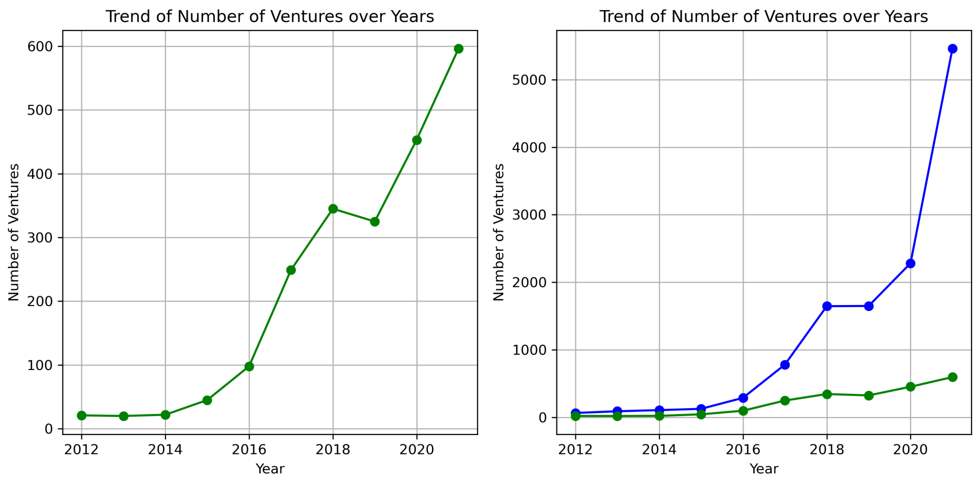


Figure 3: rends in the total number of startups that have applied to the Creative Destruction Lab and the number of startups admitted.

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.

During the last session, the nature of the mentors' choices shifts from earlier sessions. Instead of selecting startups for mentorship, the mentors assess the overall success and potential of each startup. This choice determines whether a startup should graduate from the CDL program. The decision is based on the startup's performance throughout the program, its achievement of set objectives, and its potential for future success. Graduates are selected as the top ventures from each cohort. The questions that mentors consider when choosing a startup at the final session 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 the decision-making dynamics across three sessions. At the end of the first session, mentors select the startups they wish to commit their time to. In this example, startups 1 and 3 do not receive any mentoring interests and are consequently removed from the CDL. These two startups are absent in the subsequent sessions. In the next session, mentor 2 opts for startup 5, and mentor 4 selects startup 2. In this scenario, all mentors choose startups they have not previously selected. At this session, startup 4 is eliminated from the program. In the following session, mentors 1, 2, and 4 choose startup 2. In this session, mentor 4 continues with startup 2, mentor 1, who had previously chosen startup 2 in the first session, selects it again, and mentor 2 opts for startup 2 for the first time. In this example, if session 3 is the final session, startup 2 would be the only startup to graduate from CDL and mentors have identified this startups as the one with potential.

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]

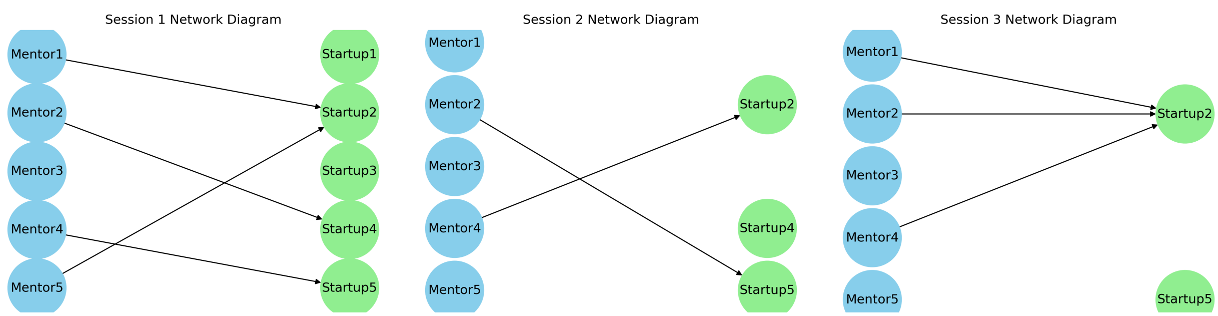
FINANCING UPDATE

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.

3 Descriptive Analysis

3.1 Data and sample

Mentorship and Performance Data: In this paper, the CDL dataset is the primary source of data for analysis. In addition to mentorship choices and advice implementations, the CDL dataset also includes information about the performance of the accepted startups after the program. These informations such as the stratup buisiness status, funding rounds and amount of raised fund are collected by CDL. Prior research has explained the details of institution and data description for CDL (Sariri (2020), Sariri (2022), Sariri Khayatzadeh (2021), Lakhani et al. (2019)).

I complement this data with Crunchbase dataset. 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, locations, industries, and descriptions of their products or services. The platform records the dates when companies were founded, giving users insights into the age of the company and its history. 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 view of the business landscape, allowing users to explore a wider range of companies and their trajectories. 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 not entered the market yet.

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 agreement is measured. If the category of the entrepreneur-proposed objective matches the mentor's finalized objective, the agreement measure for this advice is set to 1.

To motivate the model that captures the dynamics of the mentorship in the startup ecosystem, I present some preliminary evidence on the effect of mentorship on startup outcome and the effect of information and knowledge transfer on mentorship choices. I focus on patterns that suggest mentors react to arrival of new information and make their mentoring decision to trade off between learning about startups and transferring their knowledge to them.

3.2 Mentorship Effect

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 smoothed distribution of performance (logarithm of raised fund after CDL) for startups that graduates from CDL and startups that are cut

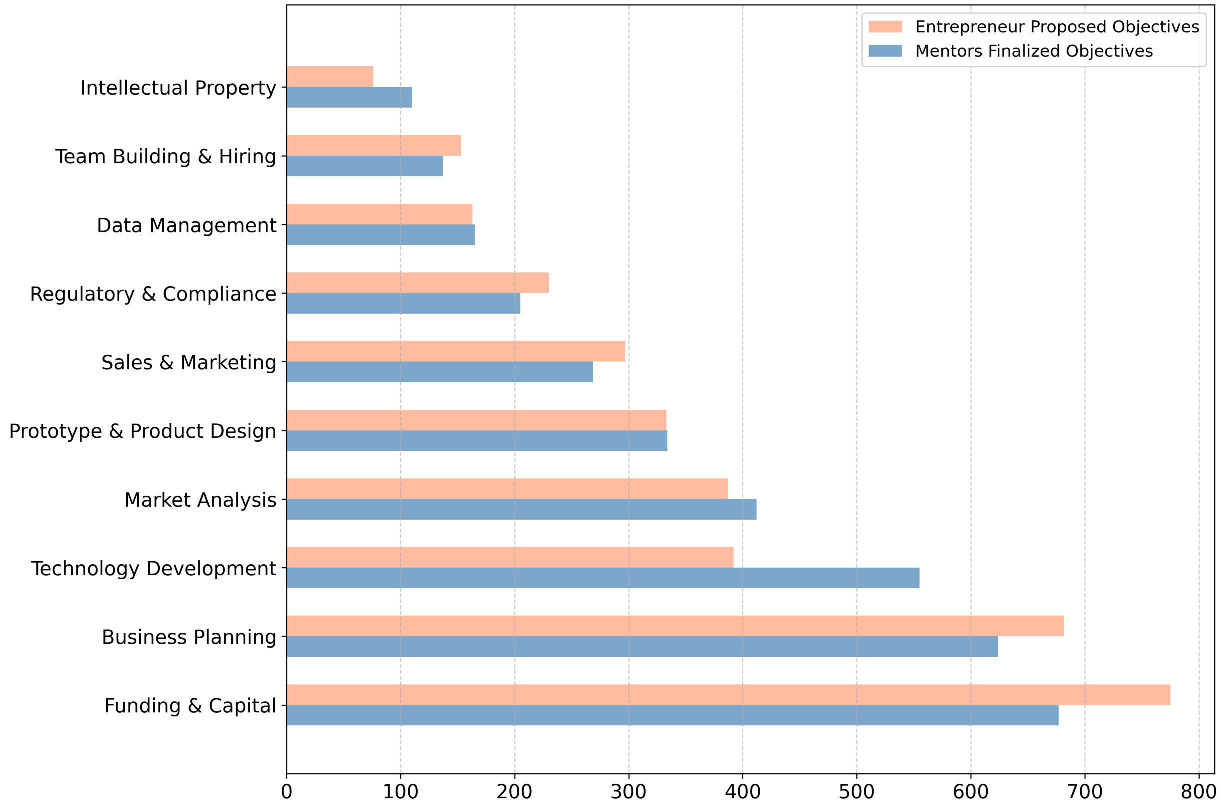
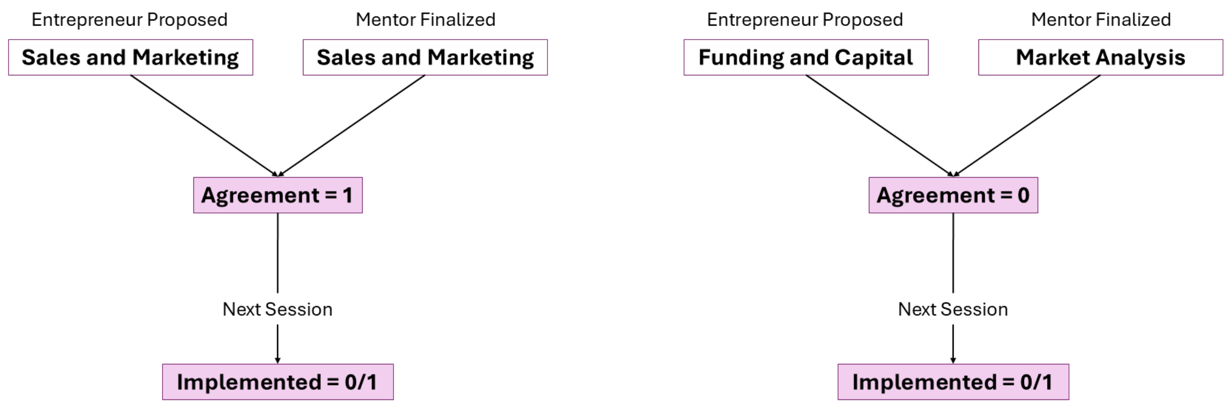


Figure 7: Distribution of advice classified into 10 different categories for both entrepreneur-proposed objectives and mentor-finalized objectives.

from CDL through the process. It seems that most variation in startups performance can be explained by a clustering startups in two groups of low and high quality, where the difference in the mean quality of the two groups is substantial. Graduation of CDL has a negligible correlation with the support of the distribution of performance, but a substantial correlation with the frequency of low and high types. 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 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 show the predicted outcomes based on the total number of implemented pieces of advice, categorized by the level of disagreement (low, moderate, high) between mentors and entrepreneurs. The left panel illustrates the predicted logarithm of funds raised by startups within one year after participation in the Creative Destruction Lab (CDL), while the right panel displays the predicted number of funding rounds secured by startups. The figures highlight how the level of agreement or disagreement between mentor advice and entrepreneur decisions influences these key startup outcomes.



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

(b) Mentors change the entrepreneur-proposed objectives.

Figure 8: Two examples demonstrating the measurement of agreement between entrepreneur-proposed objectives and mentor-finalized objectives. Agreement is set to 1 when the categories match.

In figure 12, the left panel shows the relationship between the level of agreement 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 agreement, also fitted using a Logit model.

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Figure 13 shows the distribution of Pre-CDL capital and Post-CDL raised fund within 1 year. The left figure shows the distribution for all startups and the right figure shows the distribution only for startups that have positive amount of capital before CDL and have raised a positive amount after the CDL. The pink bars show the distribution of Post-CDL raised fund. The vertical axes are frequency which represent number of startups. Based on these figures, CDL pushes startups to the extremes on the graph, meaning that the final quality of some startups is zero, while others are significantly improved. This suggests that CDL effectively distinguishes between good and bad startups.

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

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

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

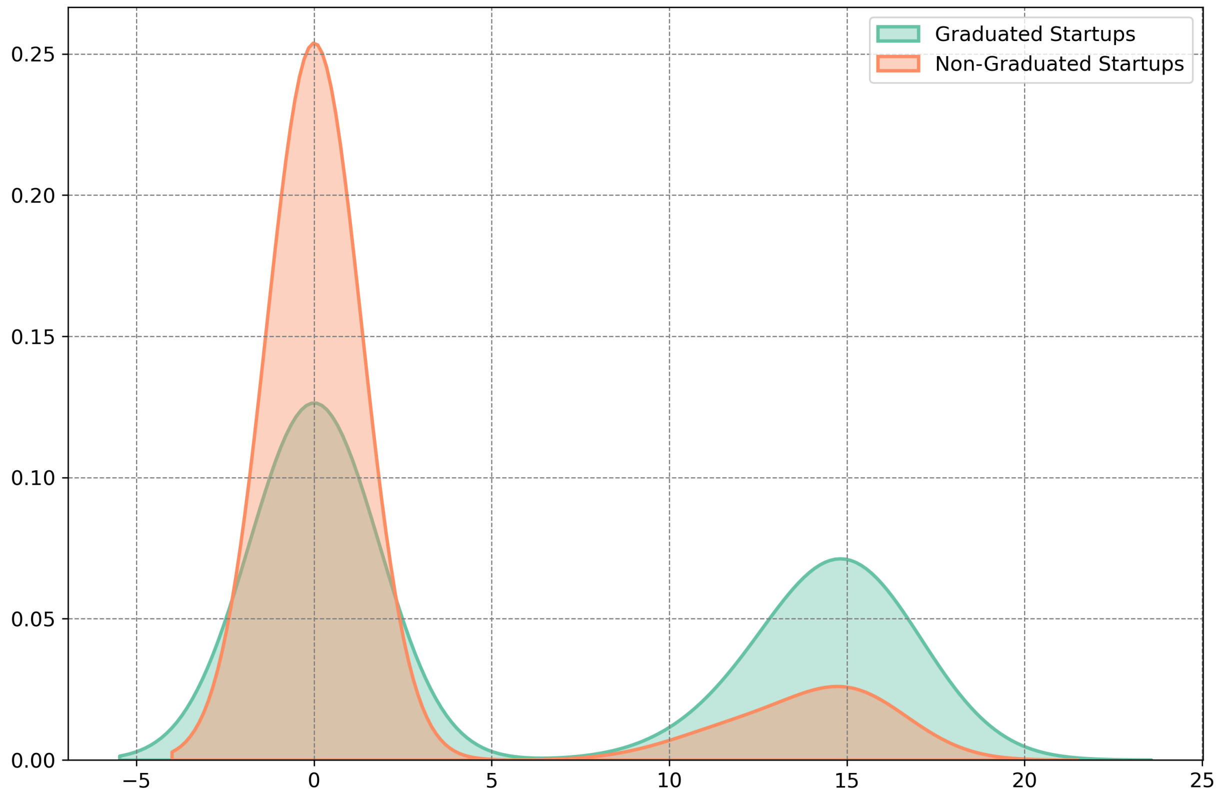
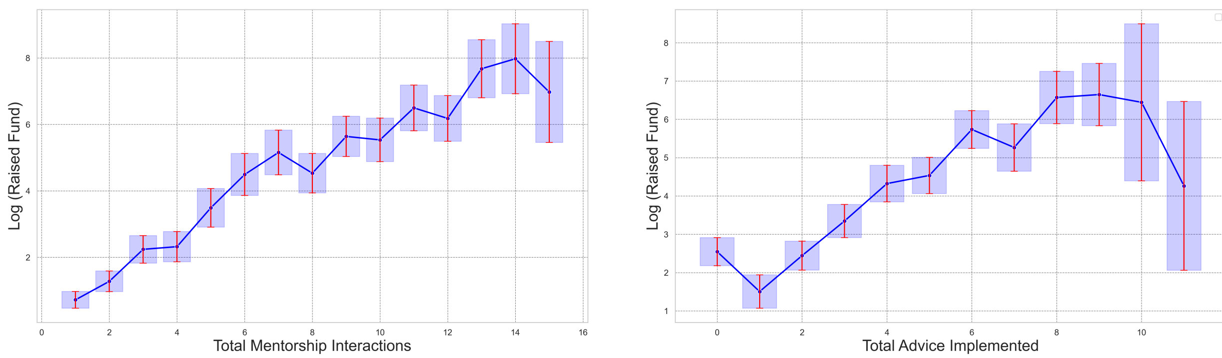


Figure 9: Smoothed distribution of the logarithm of raised funds after CDL, comparing startups that graduated from CDL and those that were cut from the program.

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 1 shows the result of the mentioned linear model. Column 1 shows the result of an OLS model. Bothe mentorship and implemented objectives 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.



(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.

3.3 Learning

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.

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

Table 2 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.

To investigate the impact of information shocks on mentoring decisions, I exploit two exogenous information shocks. The first is a positive information shock by the assignment of a startup to a Small Group Meeting (SGM) by CDL organizers. During these sessions, the assigned mentor receives additional information about the startup, which then influences their decision-making in the subsequent public session where all mentors make their mentoring decisions. The second information 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 since these absent mentors typically share their insights and evaluations. Therefore, the absence of mentors serves as a negative information shock. I investigate how mentors respond to these information shocks

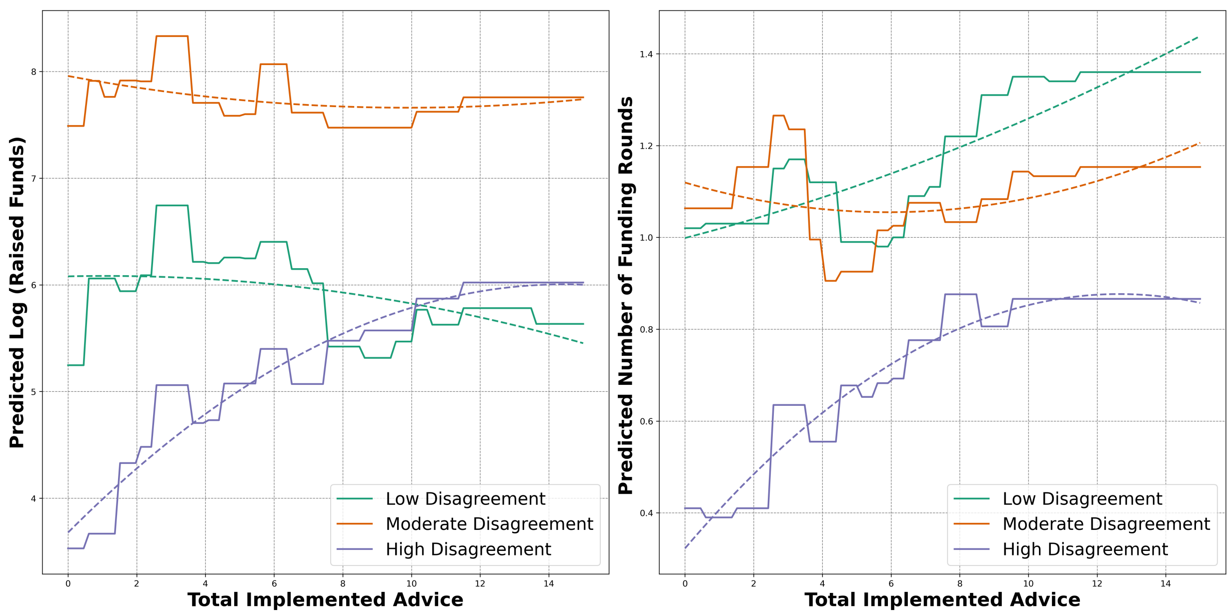


Figure 11: Predicted outcomes based on total implemented advice, categorized by the level of disagreement between mentors and entrepreneurs. The left panel shows the predicted logarithm of funds raised within one year, while the right panel displays the predicted number of funding rounds. The results are segmented into low, moderate, and high disagreement levels.

by estimating the following linear models

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

The results are presented in Table 3. 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.

The last session of the CDL program is when the mentors' decision indicate which startups are of high quality and high potential, and which ones should graduate from CDL. At this session, the incentive for quality improvement and helping is reduced, and mentors identify high-quality startups based on their knowledge. If this decision depends on the history of having direct interactions with the startup, it suggests the effect of reduced

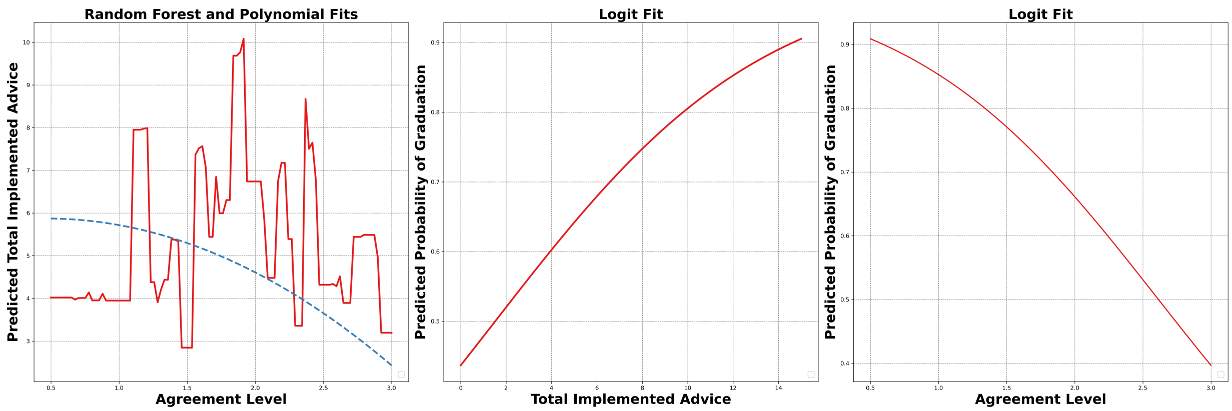
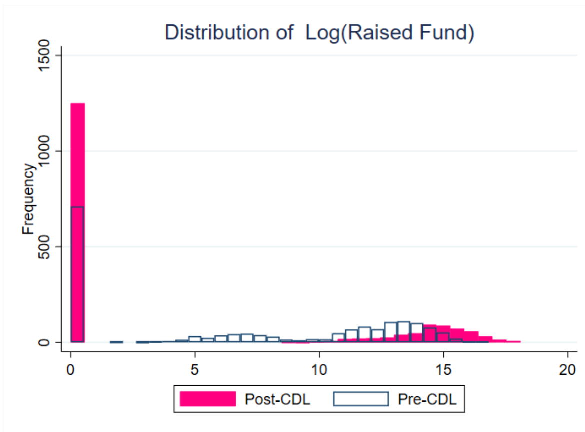


Figure 12: Relationships between agreement level, implemented advice, and the predicted probability of startup graduation at the Creative Destruction Lab (CDL). The left panel shows the Random Forest and Polynomial fits for the predicted total implemented advice based on agreement level. The middle and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

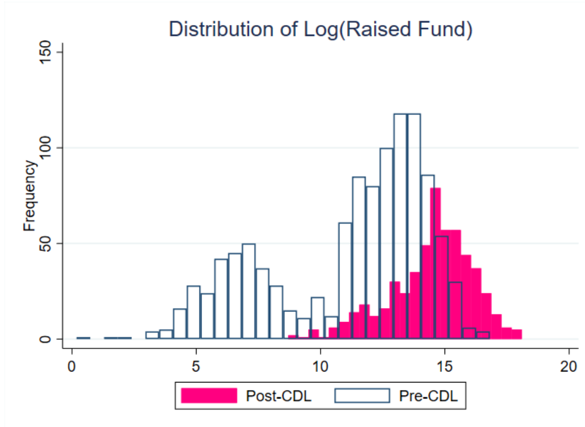
uncertainty as a result of direct interaction. I estimate the following linear model:

$$\text{MentorshipDecision}_{ijT} = \beta_0 + \beta_1 \text{History}_{ijT} + \epsilon_{ijT} \tag{4}$$

Table 4 shows a correlation between having a mentorship history with a startup and an increased probability of choosing that startup, even after controlling for the true final quality. This pattern might reflect the influence of direct information on reducing uncertainty. In Column 3, I use meeting a startup for the first time through an SGM as an instrument for having a mentorship history with that particular startup. This demonstrates a positive causal effect of interaction on the likelihood of choosing that startup.



(a) All startups



(b) Startups that had positive capital before CDL and raised a positive amount after CDL

Figure 13: Distribution of logarithm of Pre-CDL capital and logarithm of Post-CDL raised funds within one year.

	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 1: 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 2: 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)	(2)	(3)	(4)	(5)
	vote_mentorship	vote_mentorship	vote_mentorship	vote_mentorship	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 3: 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.

	Mentorship Vote		
	(1)	(2)	(3)
	OLS	OLS	IV: SGM
History	0.268***	0.268***	0.419***
	(0.0162)	(0.0162)	(0.0418)
Log(Post-CDL Raised Fund) × History	-0.00477***	-0.00471***	
	(0.00154)	(0.00154)	
Log(Post-CDL Raised Fund)	0.000953***	0.000915***	
	(0.000248)	(0.000250)	
Cohort_FE	Y	Y	Y
Site_FE	Y	Y	Y
Stream_FE	Y	Y	Y
Mentor_FE	Y	Y	Y
Challenge_FE	N	Y	Y
N	31433	31433	31433

Standard errors in parentheses

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

Table 4: Correlation between having a mentorship history with a startup and an increased probability of choosing that startup, even after controlling for the true final quality. Column 3 uses meeting a startup for the first time through a Small Group Meeting (SGM) as an instrument for having a mentorship history, showing a positive association between interaction and the likelihood of choosing that startup.

4 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 .

4.1 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:$Q_j^f = exp(q_j^f)$.

$$q_j^f = q_{j1} + \omega_1 \cdot D_j + \omega_2 \cdot A_j + \epsilon_j \tag{5}$$

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 each mentorship on the true quality of startup and measures the value added of mentorship through quality improvement. $A_j = \sum_t a_{jt}$ 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. ω_2 captures the effect of accomplishing these tasks on 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.

Despite the assumption of exogeneity, it is important to recognize the potential for endogeneity problems if ϵ_j were to be correlated with the mentorship decisions during the program. Specifically, endogeneity can arise if: $E\left(D_j \cdot \epsilon_j\right) \neq 0$

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.

4.2 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.

4.2.1 Quality Improvement

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

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

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 5 is the summation of these shocks: $\epsilon_j = \sum_t \epsilon_{jt}$.

4.2.2 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 know and observe the effect of their mentorship on quality improvement ω_1 and the learning is about the initial quality q_{j1}:

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

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 captures a simple learning processes that 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.

4.2.3 Mentors' Decisions:

During the program, mentors decide at each session whether to mentor a particular startup or choose an outside option. The vector of state variables includes μ_{ijt}: Mentor i's belief about the quality of startup j at time t, and S_t: Set of available startups at time t. 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}). The incomplete information assumption in this model means that mentors start with some initial uncertainty about the quality of startups and update their beliefs based on the signals received from their direct interactions and shared information from other mentors. Mentors choose whether to choose a startup or not simultaneously. Each mentor's decision is made independently based on their updated beliefs and the information available from previous sessions. The term incomplete information in this model refers both to the initial uncertainty about startup quality and the lack of observation of other mentors' current decisions within the same session.

Myopic mentors make decisions based solely on their current knowledge and immediate rewards without considering future implications. At period t (Mentorship Session), mentor i's utility from mentoring an available startup j or choosing the outside option is:

$$\begin{aligned} U_{ijt}(d_{ijt} = 1) &= \mu_{ijt} - c_{ijt} + \eta_{ijt_1} \\ U_{ijt}(d_{ijt} = 0) &= \eta_{ijt_0} \end{aligned} \tag{8}$$

Where c_{ijt} is mentor i's cost of mentorship. In this myopic decision-making framework, 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:

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

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 each session is eligible for graduation. The 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.

The success of the mentorship program can be evaluated by the total number of startups that graduate and the quality of these startups. The expected total quality of graduated startups is given by:

$$\sum_j g_j \cdot q_j^f$$

Where g_j is the graduation status of startup j, and q_j^f is the final quality of startup j. This approach to evaluating the mentorship program highlights the importance of each session in contributing to the startup's progress and the mentors' decisions in shaping the final outcomes. By understanding the value of each session, program designers can optimize the structure and content of the mentorship program to maximize its impact on the startups' success.

4.2.4 Entrepreneurs Implementation of Advice

In this section, I propose a binary choice model of the advice implementation. The entrepreneurs receive advice in the form of objectives to accomplish. 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, their level of disagreement with the advice, and the type of advice given. At each session, an entrepreneur receives three piece of advice than are ranked based on their priority. I assume the decision to implement each piece of advice is made independently of other advice and is time independent. Let a_{jr} be the indicator variable that takes the value 1 if entrepreneur j chooses to implement advice r, and 0 otherwise.

In this model, entrepreneurs decision on proposing advice and mentors decision on whether agree or disagree with 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 disagreement and type of advice. For example for easier types of advice, entrepreneur might see more benefit in implementing even if they disagree, but for other types of advice they might choose to ignore the advice. The endogenous choice of advice by entrepreneurs and mentors can be an extension of this model to further explore the strategic choice of advice.

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

$$U_{jr}(a_{jr} = 1) = \omega_2 - IC_{r,0} \cdot \mathbf{1}\{\text{Agree}_{jr} = 0\} - IC_{r,1} \cdot \mathbf{1}\{\text{Agree}_{jr} = 1\} + \zeta_{jr_1}$$

Where ω_2 is the quality improvement gain from implementing the advice and $IC_{r,0/1}$ is the perceived implementation cost that depends on how difficult the task is and also on whether the entrepreneur agrees with the advice. $IC_{r,0/1}$ is indexed by both the type of advice and the level of agreement. This means that each combination of advice type and agreement 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 advice and different levels of disagreement.

Different types of advice (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 entrepreneur's level of agreement with the advice affects their willingness to implement and perceived cost of implementation. If an entrepreneur agrees with the advice, they are more likely to perceive the implementation as less costly. If they disagree, the perceived cost increases as it may require a change in their current approach or because they do not think this is the best strategy to implement.

4.3 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 advice 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:

$$\max_{\{d_{ijt}, a_{jt}\}} W(d_{ijt}, a_{jt} : \forall i, j, t) = \sum_i \sum_j g_j(d_{ijt}, a_{jt}) \cdot q_{jT}(d_{ijt}, a_{jt}) \tag{9}$$

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

4.3.1 Welfare Loss

The welfare loss 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:

$$\text{Welfare Loss} = W(d_{ijt}^{SP}, a_{jt}^{SP} : \forall i, j, t) - W(d_{ijt}^{*}, a_{jt}^{*} : \forall i, j, t) \tag{10}$$

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.

5 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 mentorship on startup quality. ω_2: The effect of implemented advice 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 disagreement. 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.

5.1 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 5 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.

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

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_j1 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:

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

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.

5.2 Estimating the initial beliefs

In a simple version of the model with homogeneous myopic mentors, the mentors' first session mentorship choice for a specific startup is based solely on the 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.

5.3 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 experiences. 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 $(\lambda - \gamma\lambda)b_{j1}$.

5.4 Estimating the perceived implementation costs

I generate the agreement variable Agree_{jr} by comparing the category of advice proposed by the entrepreneur and the advice given by the mentor. Specifically, I use the Cohere API to categorize both the advice proposed by the entrepreneur and the advice given by the mentor into one of the 10 predefined categories. For each piece of advice, I compare the category proposed by the entrepreneur with the category of the mentor's advice and create a binary variable Agree_j which takes the value 1 if the categories match (agreement) and 0 if they do not match (disagreement).

The probability of implementing each piece of advice is estimated using a frequency estimator. This is calculated as the ratio of the number of times advice r was agreed/disagreed with and implemented to the total number of times advice r was given and agreed/disagreed with:

$$\hat{p}(r, \text{agree/disagree}) = \frac{\text{Number of implemented and agreed/disagreed } r}{\text{Total } r \text{ advised and agreed/disagreed}}$$

Given the known parameter ω_2, the perceived implementation cost $IC_{r,agree}$ for each combination of category of advice and agreement can be estimated using the logit model equation. This approach allows me to estimate the perceived implementation cost associated with each category of advice and level of agreement based on the observed implementation frequencies in the data.

6 Results

6.0.1 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, each additional unit of mentorship increases the final quality by $\hat{\omega_1} = 0.25$ units and each implemented advice by startup improves the quality by $\hat{\omega_2} = 0.67$. 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 6.0.1 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
tot_mentorships_v	0.415***	0.225**	0.253**	0.232**	0.260**
	(0.0387)	(0.109)	(0.106)	(0.109)	(0.106)
sum_obj_status_v	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.

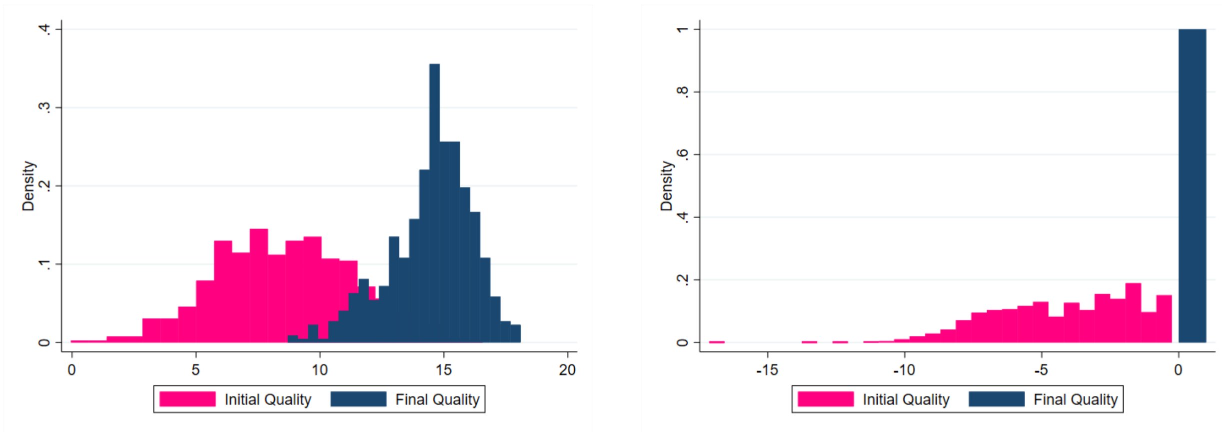
	Mentorship Interactions	Implemented Objectives	Final Quality
	(1)	(2)	(3)
	First Stage	First Stage	2SLS
Mentorship Interactions			0.260^{**}
			(0.106)
Implemented Objectives			0.658^{***}
			(0.245)
Absent previous mentors	1.416^{***}	0.267^{***}	
	(0.0518)	(0.0365)	
SGM assigned mentors	0.147^{***}	0.145^{***}	
	(0.0122)	(0.00863)	
Has Patent	0.161	-0.153	0.944^{**}
	(0.250)	(0.176)	(0.473)
Has Prototype	-0.634	1.209^{*}	-3.887^{**}
	(0.915)	(0.644)	(1.754)
No. of Founders	-0.00642	-0.0380	0.283
	(0.101)	(0.0708)	(0.190)
No. of Technologies	0.247	-0.889	3.299^{**}
	(0.829)	(0.584)	(1.579)
Log(Pre-CDL Capital)	0.0266	0.0110	0.00159
	(0.0390)	(0.0275)	(0.0738)
IMR	-0.615	4.396	-23.14^{**}
	(5.796)	(4.082)	(10.98)
Cohort_FE			
Site_FE			
Stream_FE			
Challenge_FE			
N	1778	1778	1778

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 14 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 14: 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.

6.0.2 Initial beliefs

I use the Hotz-Miller inversion method to recover common initial beliefs (equation 12). 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 15 shows three key distributions: True Initial Quality (q_1): Represented by the orange hatched bars. Common Initial Belief about q_1 (μ_1): Represented by the solid blue bars. Initial Bias ($b_1 = q_1 - \mu_1$): Represented by the grey dotted bars.

The orange hatched 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 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.

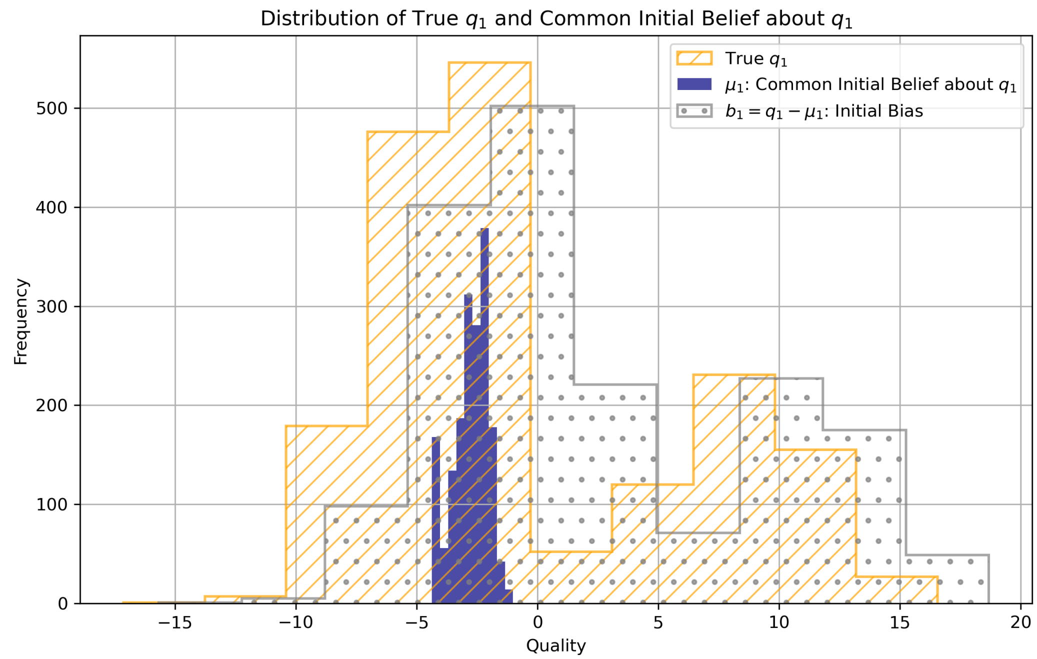


Figure 15: Distributions of: True Initial Quality shown by the hatched bars, Common Initial Belief about the Initial Quality represented by the solid bars, and Initial Bias the difference between the true quality and the common belief shown by the dotted bars.

The solid blue 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.

The grey dotted distribution represents the initial bias, which is the difference between the true initial quality and the common initial belief. The bias distribution shows a broader range, similar to the true initial quality distribution. Positive biases indicate startups that were undervalued by mentors, whereas negative biases indicate those that were overvalued. The distribution of biases suggests that there are significant discrepancies between the true quality and the mentors' initial beliefs, with biases spread across a wide range.

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 (b_1) 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.

6.0.3 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 6.0.3 shows the estimation result of a conditional logit model using MLE. Assuming that $\hat{\omega_1} = 0.25$ and $\hat{\omega_1} = 0.67$ from the first step, table 6.0.3 shows a learning rate of $\hat{\lambda} = 0.028 = 28\%$, a degree of information sharing of $\hat{\gamma} = 0.7$ 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:

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

Conservative Mentors: The findings that initial beliefs are centered with less variation and are mostly negative (indicating undervaluation) shows conservatism bias in mentors initial evaluation. This conservative evaluation could be due to several factors, including risk aversion and the high uncertainty associated with early-stage startups. The slow update in their beliefs is also consistent with this conservative prior (Edwards (1968), Barberis et al. (1998), Ikenberry et al. (1995)). Mentors' slow response to new information suggests a preference for accumulating more evidence before significantly changing their evaluation. Overall, the low learning rate and small variance in initial evaluations provides empirical support for the presence of conservatism bias among mentors.

Facilitating learning within mentorship programs can effectively mitigate conservatism bias by encouraging mentors to update their beliefs more rapidly and accurately based on new information. For instance, incorporating structured feedback mechanisms, where mentors receive regular updates on startup performance and outcomes, can help mentors adjust their evaluations more quickly. Accelerators can implement such strategies, providing continuous performance reviews and leveraging data analytics to guide mentorship. By integrating these practices, startup accelerators can reduce the conservatism bias affecting mentor judgments.

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.

6.0.4 Perceived Implementation costs

The results of the estimation for the perceived implementation costs of advice across different categories and agreement are presented in Figure 16. I have estimated the costs based on the priority of the advice. 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 ("Agree=1") or not ("Agree=0").

Negative effective costs in this model suggest that certain categories of advice are perceived by startups as beneficial in ways that go beyond the direct improvements in quality captured by parameter ω_2. 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.

6.1 Counterfactual Experiments

6.1.1 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. Myopic 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. Moreover, the quality improvement is further decomposed into contributions from mentorship ($\omega_1 D$) and task implementation ($\omega_2 A$).

$$\begin{aligned} W^m - W^{cf} &= \sum_j g_j^m \cdot q_{jf}^m - \sum_j g_j^{cf} \cdot q_{jf}^{cf} \\ &= \sum_j q_{jf}^{cf} \cdot (g_j^m - g_j^{cf}) + \sum_j g_j^m (q_{jf}^m - q_{jf}^{cf}) \\ &= \sum_j q_{jf}^{cf} \cdot (g_j^m - g_j^{cf}) + \omega_1 \sum_j g_j^m (D_j^m - D_j^{cf}) + \omega_2 \sum_j g_j^m (A_j^m - A_j^{cf}) \end{aligned} \tag{13}$$

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:

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

Figure 17 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 advice 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 18 shows the heterogeneity of decomposed gains across different sectors. Some sectors generate more value through resolving the uncertainty compared to other sectors. Figure 19 shows the path of learning gain for selected streams.

6.2 Value of Advice on Entrepreneurial Choice

In this section, I evaluate the welfare implication of helping entrepreneurs to implement their own strategy instead of the advice given by mentors. 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 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 mentor-provided advice in driving strategic change.

I simulate a counterfactual of assigning the advice proposed by entrepreneurs as the objectives and recalculating the perceived benefit and implementation rates under this scenario. Given the absence of a dynamic model for advice 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 advice. The perceived net benefit under the counterfactual scenario is recalculated by assigning the cost associated with the entrepreneur-proposed category under the agreement condition. Using the recalculated perceived net benefits, I compute the counterfactual probability of implementation for each advice. To isolate the effect of change in advice, 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 advice changes or the advice 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 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 allowing mentors to influence 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 give advice on 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 based on their assessment and advice. The counterfactual scenario removes this option where mentors only give advice on implementing the entrepreneur's proposed strategies. 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 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. he plot shows that most of the program-sessions benefit from advice on entrepreneurs decision-making. 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 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 welfare gains across different streams when mentors provide advice on the objectives proposed by entrepreneurs. 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. This can inform policymakers and investors about targeted support for high-potential industries.

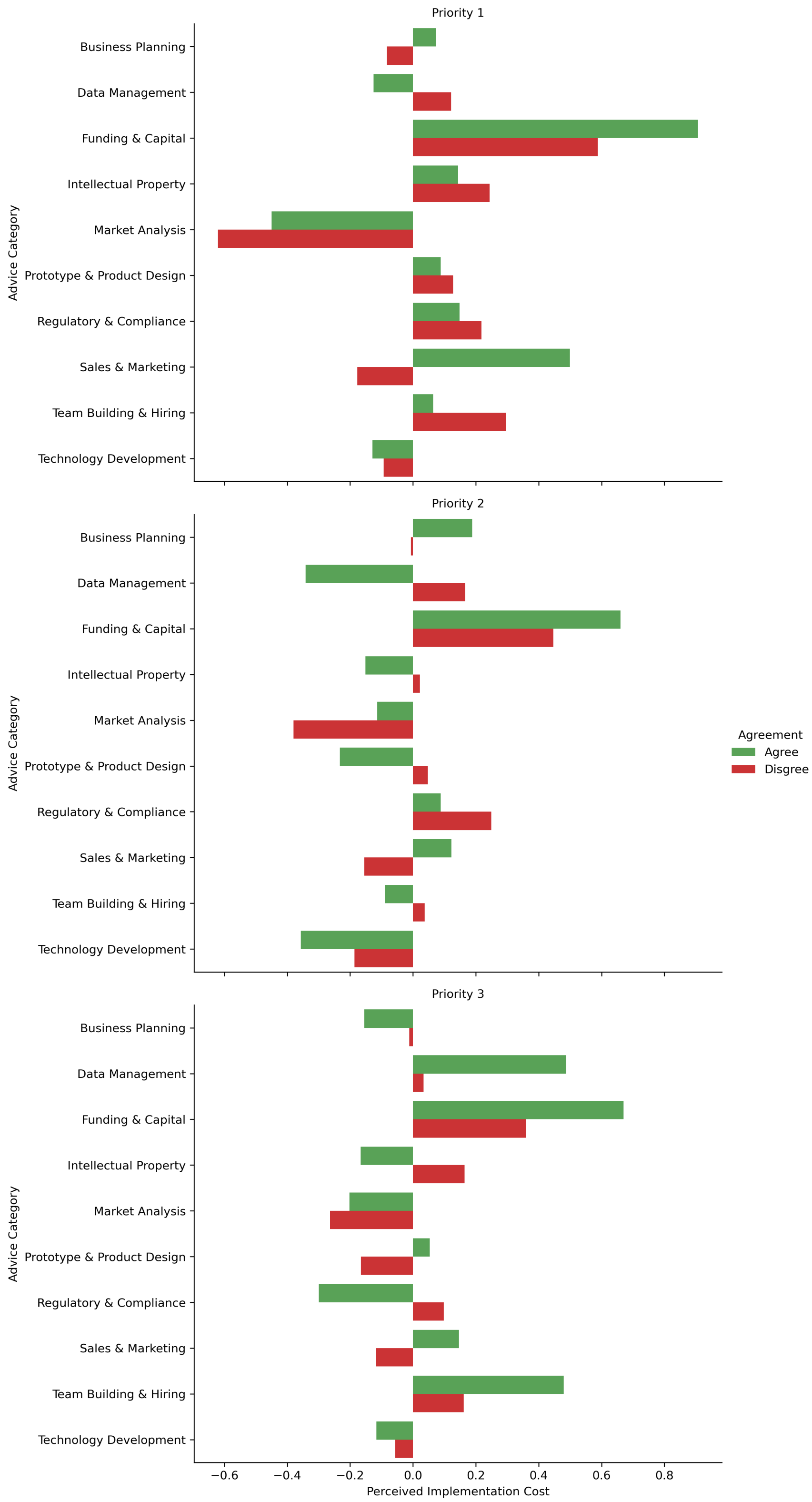


Figure 16: Estimated perceived implementation costs of advice across different categories and levels of agreement. The costs are estimated based on the priority of the advice. The chart compares the implementation costs for advice aligned with the entrepreneur's proposed objective (Agree=1) versus advice that was not aligned (Agree=0)

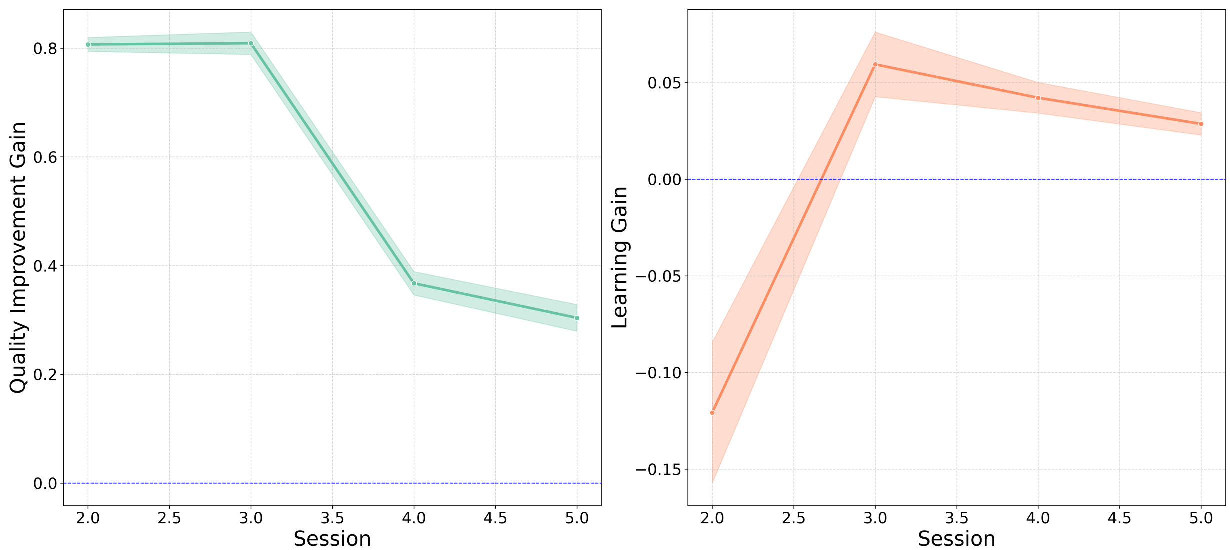


Figure 17: Trend of welfare gains generated through multiple sessions of the Creative Destruction Lab (CDL). The average quality gains for a startup from the first session are around 80% and decrease over time. The average learning gain shows more variation across sessions. Mentors identify startups that are, on average, 2.3% higher in quality after additional mentorship sessions compared to those selected without these sessions.

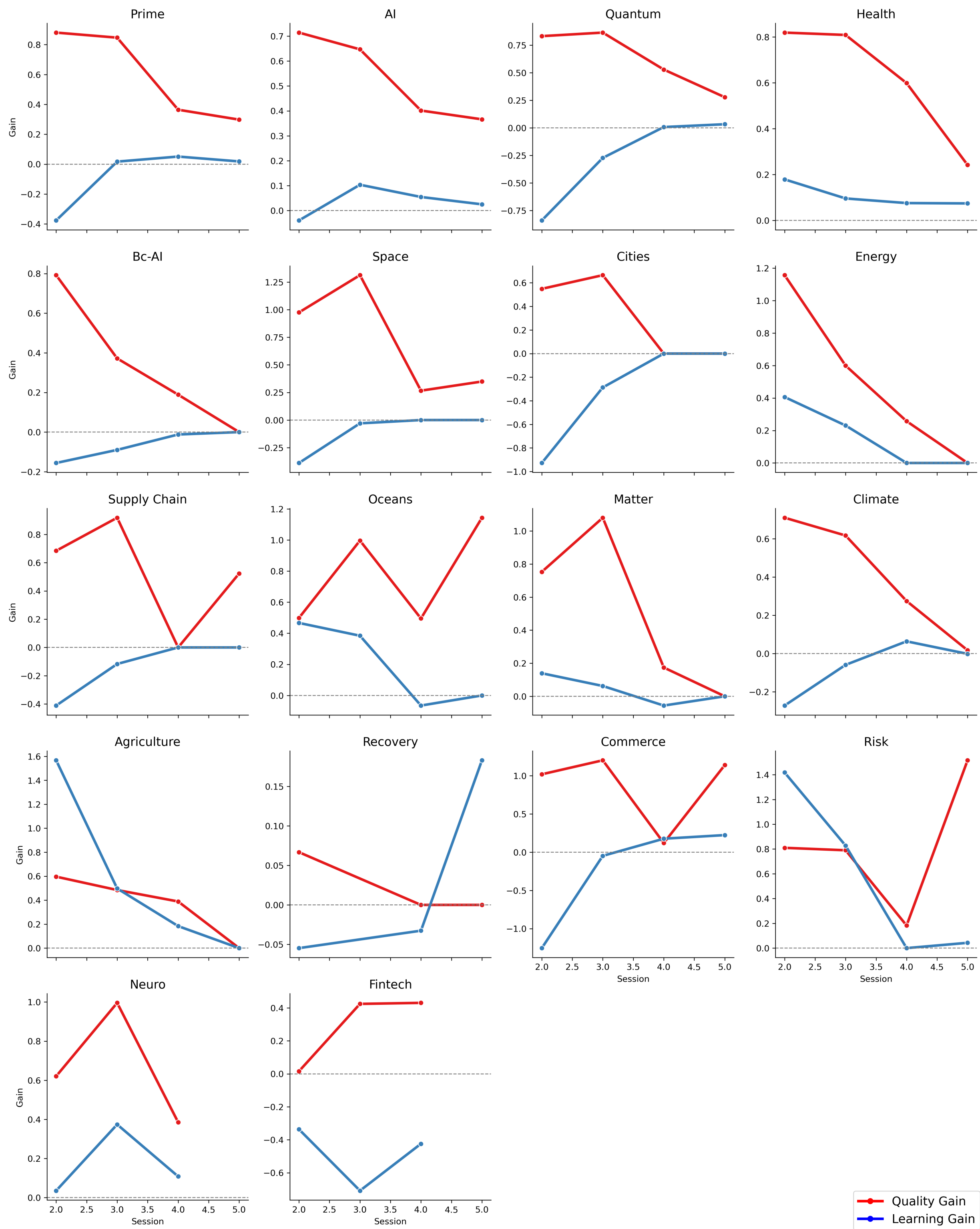


Figure 18: Heterogeneity of decomposed gains across different sectors.

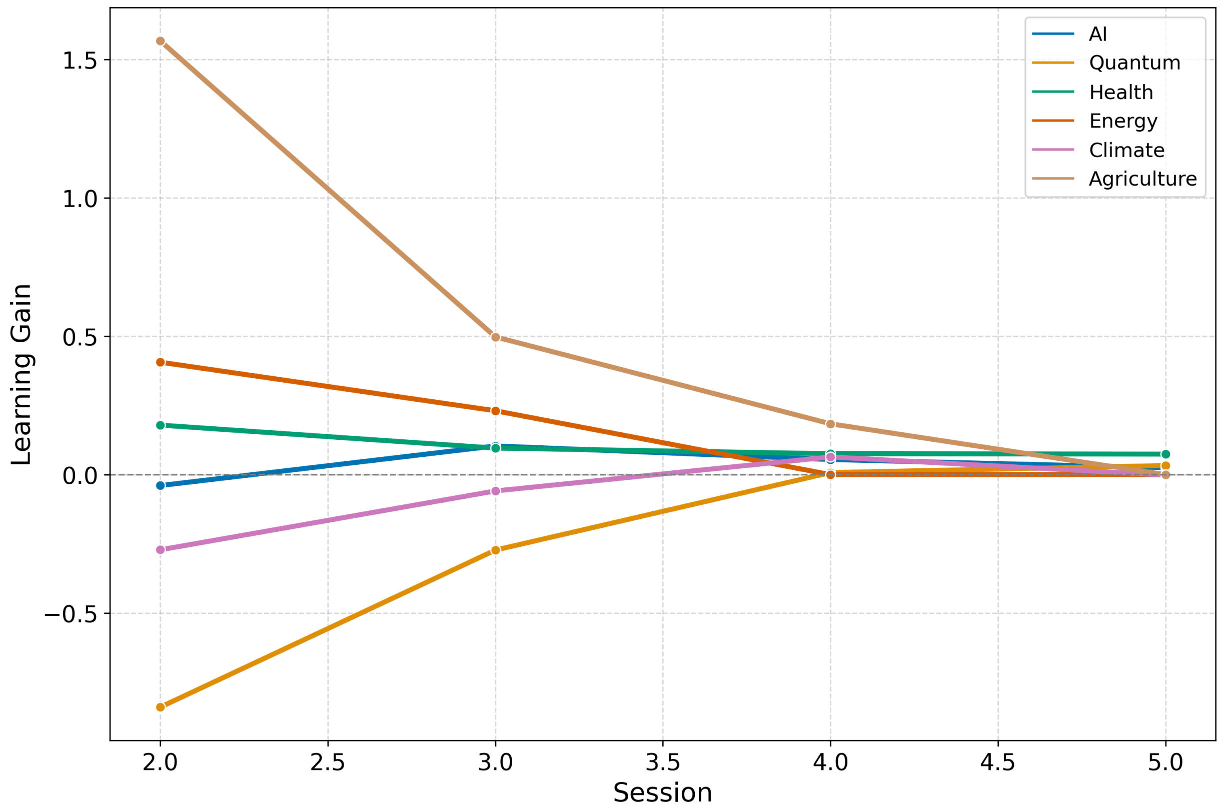


Figure 19: Path of learning gains for selected sectors.

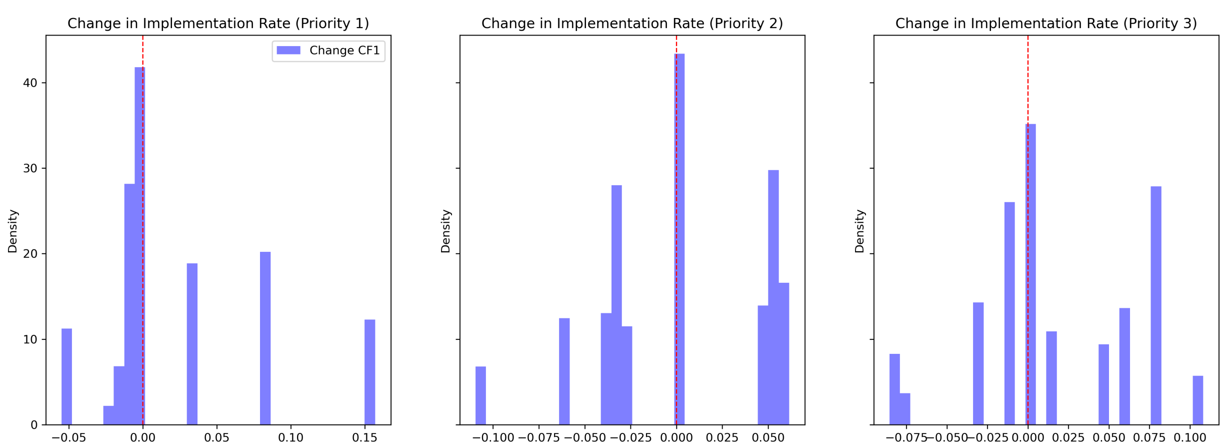


Figure 20

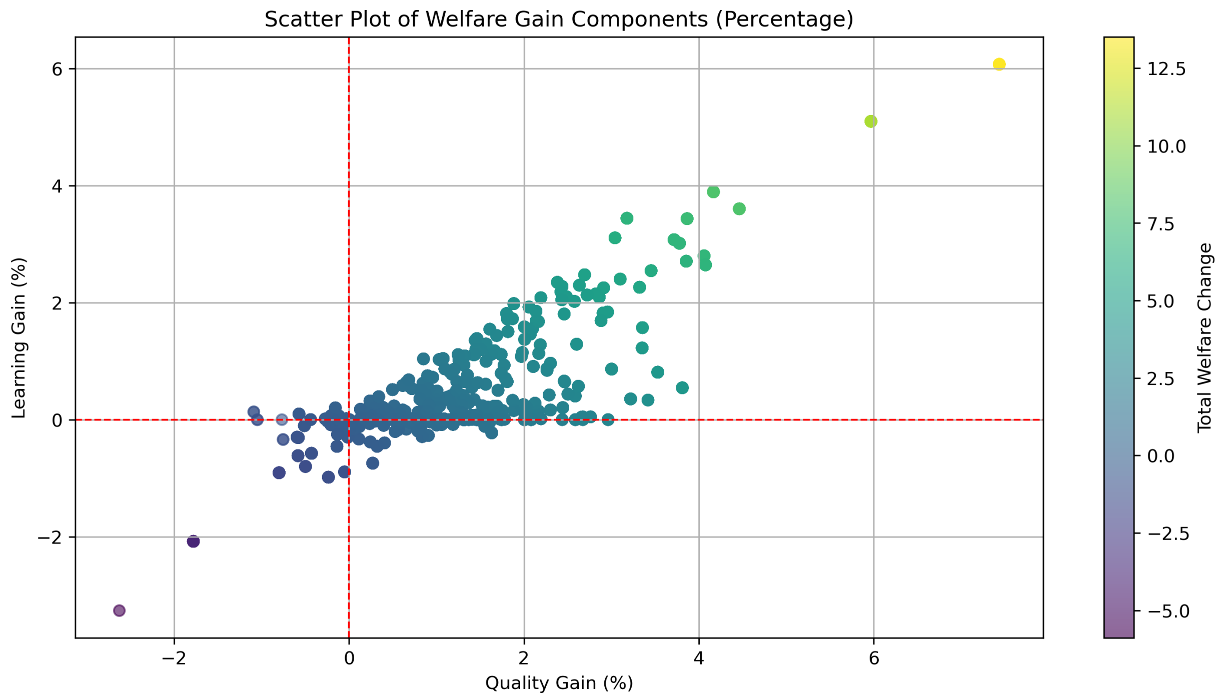


Figure 21: The percentage of Quality Gain versus percentage of Learning Gain, colored by the percentage of Total Gain. Each dot on the graph represents a program-session. Positive values are the average welfare gained for a whole program-session by allowing mentors to give advice on the entrepreneur's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

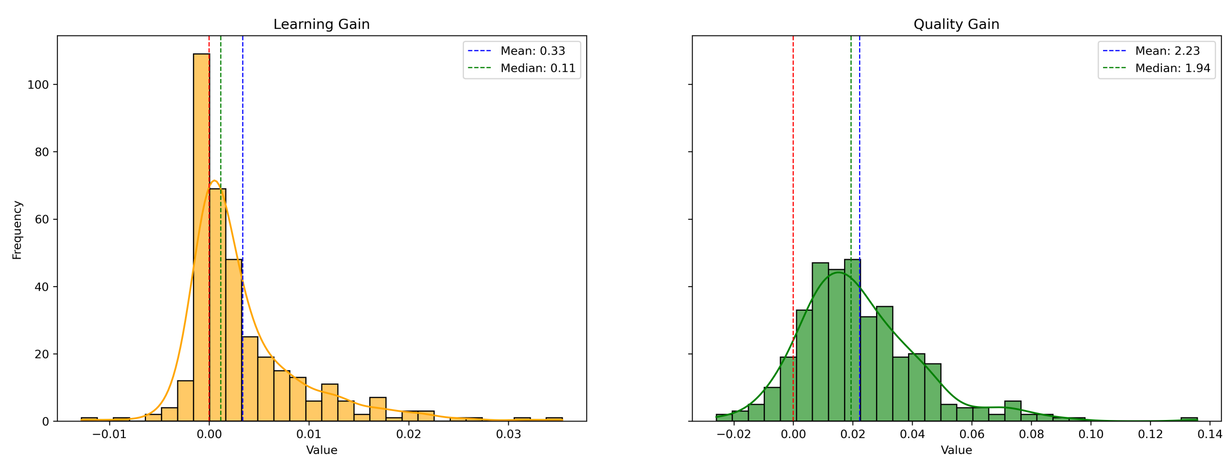


Figure 22: The distribution of the gains from advice on entrepreneurial choice. This is the gain associated with mentors better identifying the high quality startups in the final session. The second histogram shows the gain associated with the change in implementation rate which translates into changes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

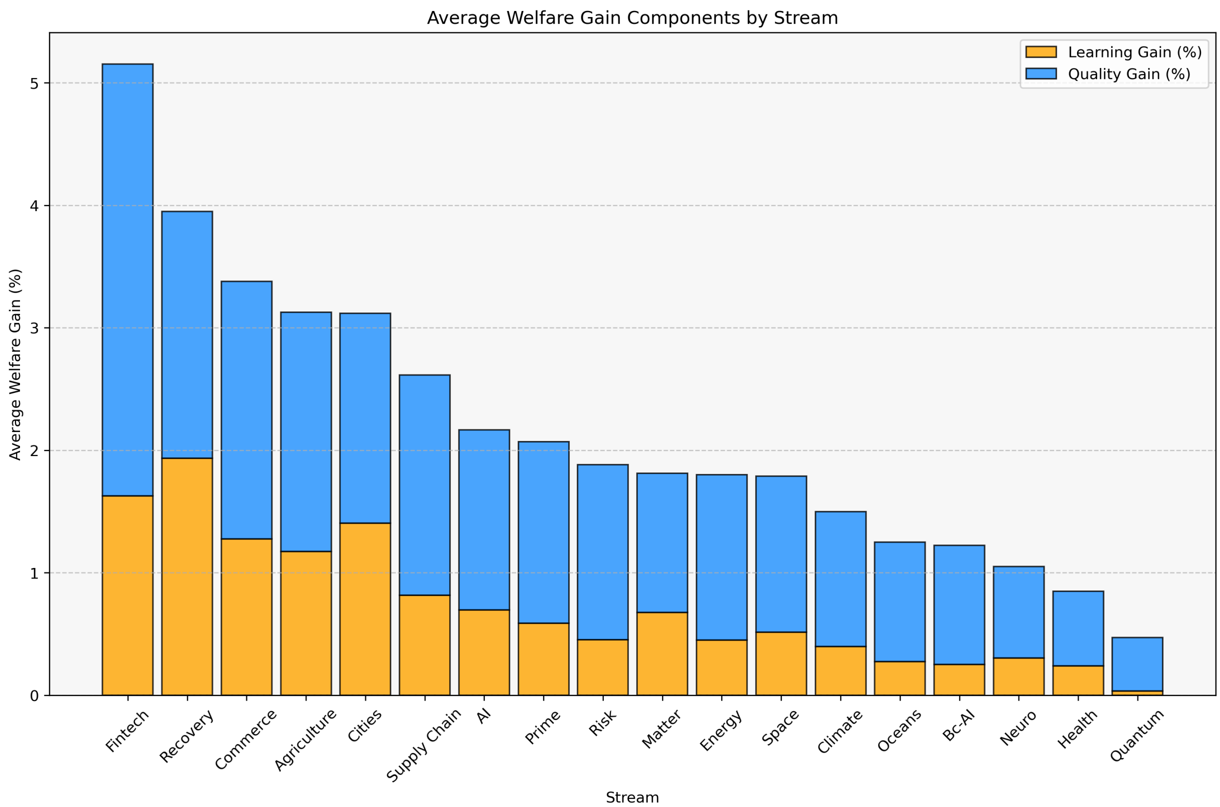


Figure 23: The average welfare gains across different streams.

7 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.

Moreover, I show that the advice provided by 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.

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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