The Economics of Advice: Evidence from Startup Mentoring

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Abstract

This paper examines the role of advice in early firm development and growth, drawing on detailed data from a global program where angel investors and venture capitalists mentored founders over several months. Leveraging variation in mentors' availability to support startups due to personal scheduling conflicts, I find that advice significantly improves startups' future market performance. To explore how advice shapes early firm development, I develop a novel typology of startup activities, finding that a defining element of mentors' advice is to do less and learn more. Although angels and VCs are consistent in this message, they differ significantly in when they choose to advise startups in achieving their business objectives. Angels are more likely than VCs to help founders design and execute product market experiments, while VCs provide more mentoring support on business analysis and planning tasks. I find evidence consistent with the hypothesis that experimentation is a skill developed via learning-by-doing, and angels have a skill advantage in that domain due to having more operational experience.

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1 Introduction

Advice is a cornerstone of entrepreneurship. It is a staple component of both private sector accelerators and public sector economic development initiatives. The widespread adoption of these programs underscores the high demand for mentoring, but these programs are not the only systematic providers. Providing advice is also a primary function of startup investors, who are instrumental in shaping early firm development. Despite its entrenched role in entrepreneurship, advice remains a surprisingly uncharted territory. The present paper is, to my knowledge, the first to systematically measure and analyze advice to identify its effect on firm performance, and characterize its nature and provision by early-stage investors.

Data consist of detailed, hand-collected information on how 192 venture capitalists and angel investors mentored 253 early-stage, high-technology startups in building their businesses over approximately eight months. The setting is a global entrepreneurship program for technology-based startups called Creative Destruction Lab ("CDL"). Since its inception in 2012, approximately 3,500 startups have participated in CDL, collectively generating over $30 billion in equity value. The program involves four day-long meetings held every 8 weeks at participating universities, where mentors help founders prioritize measurable business objectives and select startups to advise on how to achieve those goals. For startups, the dataset includes pre-program characteristics, longitudinal operational and financial details during the program, and post-program market outcomes. For mentors, it captures their educational and professional histories, codified verbal advice given to founders, and the panel of 7,914 mentoring decisions to assist startups with achieving their prioritized business objectives. To analyze advice, I develop a novel typology of entrepreneurial activity that links 4,542 granular startup activities to the foundations of strategy. The sample is diverse, covering startups in fields such as quantum computing and medical devices, performing activities that range from business planning to technology validation and financing. The richness of this setting, with its detailed tracking of key variables, provides a unique opportunity to gain new insights not only into business advice, but also into critical processes in early firm formation and growth.

As a preview of the main results, I find that mentoring drives startup success. To establish causal evidence, I exploit variation in the personal schedules of the mentors to instrument for the amount of mentoring time startups received. I find that an additional hour of mentoring increases the probability of a startup raising more external capital than the median startup in its technology domain by 3%, and improves the likelihood of staying in business four years later by 1%. These results are consistent across a range of alternative specifications and estimation methods. By analyzing the business tasks founders would have pursued without mentor advice, I find that the characteristic element of mentor advice is to do less and learn more. While founders tend to prioritize implementing their ideas and acquiring resources, mentors emphasize activities that generate information—from low-cost exploratory efforts to complex market validation experiments.

Although mentors are generally consistent in their advice to founders to increase focus on business analysis and experimentation, I find significant differences between angels and VCs in the business objectives they choose to personally help startups achieve. Angels are more likely than VCs to mentor founders on designing and executing business experiments, while VCs focus more on analytical tasks such as market research and organizational planning, as well as developing organizational structure. Consistent with Gans (2018), I find that experimentation is a skill developed through learning-by-doing and angels have an advantage in experimentation due to their greater operational experience. This is important because, as documented by Camuffo *et al.* (2020), I find that experimentation reduces uncertainty about startup quality.

The contributions of this project illustrate how studying advice provides a novel lens to understanding entrepreneurial strategy. Experimentation is central to the entrepreneurial process (Kerr *et al.*, 2014; Manso, 2016), yet it is inherently costly—requiring partial commitments that can foreclose the option to abandon unpromising ideas (Gans *et al.*, 2019) or dilute high-impact innovations into incremental ones (Felin *et al.*, 2020). These costs make it challenging for entrepreneurs to balance exploration—testing new opportunities—and exploitation—refining and scaling promising ideas. Agrawal *et al.* (2021) argue that mentors can alleviate this tension by helping entrepreneurs "learn how to learn" (Nelson, 1997). My findings extend this argument by showing that the operational experience embedded in advice can be a critical mechanism for navigating the complexities of designing and running experiments. An implication for entrepreneurs is the importance of identifying and aligning the business challenges for which they need support with the expertise of their mentors or investors.

This project also advances our understanding of how investor human capital shapes early-stage firm development (Sorensen, 2007; Hochberg *et al.*, 2007). In particular, angels and VCs compete to fund scalable ideas by deploying a roughly equal amount of risk capital,[1] but they differentiate themselves by the value-added services they claim to provide (Hsu, 2004). In the absence of empirical guidance, however, theory has made conflicting assumptions about differences in their value-added potential.[2] My results serve as such guidance. If experiments are crucial in setting a path to success, angels may compete with VCs by providing early advice that is differentiated by their operating experience. This is consistent with the fact that only 7% of VCs have substantial entrepreneurial experience (Gompers & Mukharlyamov, 2022), in contrast to angels who are predominantly ex-entrepreneurs (Ibrahim, 2008; Linde *et al.*, 2000).

This paper also joins the growing body of knowledge that bridges research on accelerators (Hallen *et al.*, 2020; Hochberg, 2016; Yu, 2020) with studies on the intricate commercialization obstacles that high-technology startups face (Hsu, 2007b; Arora *et al.*, 2024; Roach & Sauermann, 2023). For example, Bryan *et al.* (2022) demonstrate that workers applying to science-based startups have difficulty assessing firms' scientific and business quality, leading to information frictions that impede efficient hiring–an information friction that experts already present in accelerators significantly reduce. On financing, too, Nanda *et al.* (2023) note disagreements between founders and investors on which experiments to prioritize, prompting some VCs to move upstream towards incubating and mentoring in-house ideas (Lerner & Nanda, 2020).

Finally, this paper contributes to the policy debate on fostering regional startup activity by addressing the widespread use—but limited success—of policies designed to incentivize investors (see Lerner (2009) and Cumming & MacIntosh (2006) for examples). These policies often overlook the human capital bundled with investment, failing to account for the drivers of value-added services

[1] A 2009 OECD report estimates the size of angel and VC markets in the U.S. at \$18.3 and \$17.7 billion, respectively, and in Europe at \$5.3 and \$5.6 billion. These statistics are consistent with a later OECD report (2011), and estimates by Mason & Harrison (2002), and Sohl (2003). Though less well known, even large VCs invest in small amounts. For example, Andreessen Horowitz, the largest VC in the world by total asset under management, has a history of seed investing, such as the \$250,000 stake it took in Instagram. In fact, Andreessen Horowitz has a dedicated seed fund, which highlights "expertise & hands-on support" as one of its top four services (see Appendix Figure B1 for a snapshot of the fund's home page). The recent proliferation of micro VCs indicate continued growth in the seed funding market (Amore *et al.*, 2023).

[2] Some theorists assume angels are arm's-length investors who provide limited or no value (Bergemann & Hege, 2005; Chemmanur & Chen, 2014), while others assume the opposite (Leshchinskit, 2002; Schwienbacher, 2009; Casamatta, 2003). The muddle also exists in practice. Regulatory guides such as the SEC (2022) underscore a more active mentoring role for VCs than angels, whereas the popular press often views substantial mentoring as a key feature of angels (e.g., New York Times, 2015). Given these conflicts, finance scholars have long called for empirical evidence on how angels and VCs differ in their value-added potential (Da Rin *et al.*, 2013).

that influence startup growth trajectories. My findings support recent theory by Hellmann & Thiele (2019), which highlights operating experience as a determinant of these services.

The findings and limitations of this study open new avenues for research. While I discuss these opportunities in more detail later, understanding *how* mentors drive startup success remains a critical question. My results point to learning—discovering and testing product-market options—as a key mechanism, consistent with the qualitative insights of Cohen *et al.* (2019). However, making causal claims about this mechanism would require randomizing startup-mentor matches, which was not feasible in my setting. I do my best in mitigating endogeneity concerns, however, by using various econometric techniques, such as fixed effect methods, sub-sample analyses, tests of alternative explanations, matching methods, and a battery of robustness tests against alternative measures and specifications. Therefore, this study lays a foundation for future research to deepen our understanding of why some mentors are more effective than others in helping early-stage startup build their businesses.

The rest of this paper is organized as follows. The next section describes the empirical setting and sample characteristics. Section 3 presents a new typology of startup activities to measure advice. In Section 4, I describe how I identify the effect of mentoring on startup success. Then, I present the performance results in Section 5, the nature of advice and its provision in Section 6, and tests of alternative explanations in Section 7. The final set of findings in Section 8 provides evidence of the comparative role of VCs in driving organizational structure. Section 9 discusses the broader implications and opportunities for future research.

2 Empirical Setting

The setting is a global entrepreneurship program for technology-based seed-stage startups called Creative Destruction Lab ("CDL"). CDL is a nonprofit that operates in business schools ("sites") and is steered by faculty. Since its inception in 2012, CDL has grown from a solitary business school and 24 alumni, to 13 business schools across seven countries, with 28 specialized technology streams, and more than 3,500 alumni estimated to be worth over $30 billion. The essence of CDL is four in-person "sessions" every 8 weeks in which mentors advise founders in prioritizing three measurable business objectives to focus on for the next 8 weeks, then select startups to further advise on how to achieve those objectives. A fifth and final graduation session concludes the program year.

Admission to CDL is open to startups from anywhere around the world and includes submitting a detailed application and participating in business and technical assessment interviews. Finalists are offered admission to a technology "stream" at a unique "site" (hereafter, a "track").[3] Each stream assembles mentors with relevant domain expertise, such as prior investment history in the same technology domain.

Data used in this project are from the 2018-2019 cohort, the latest and largest cohort available when I began collecting data. Startups are from seven technology streams, including AI, space, and quantum computing, and one general stream for startups that do not fit in any of the specialized streams. There are 148 VC and 44 angel mentors,[4] and 253 startups, representing all 14 tracks in the program year. Mentors are predominantly from established ecosystems such as Silicon Valley, Boston, and Toronto, and are not permitted to delegate their mentoring role to an associate. Each track has an average of 18 startups (SD = 4.8) and 19 mentors (SD = 6.8), with 75% of mentors participating in a single track, 18% in two tracks, and the remaining 7% in three or more tracks. Appendix A provides additional details about CDL and sample construction.

2.1 Mentoring Process

A week before each session, mentors in each track receive updated dossiers like the one in Figure 1 on every startup in their track. These dossiers outline the founders' proposed objectives for the upcoming 8 weeks, the status of the previously finalized set of objectives, and updated financial details. Mentors are asked to familiarize themselves with each firm's progress and formulate their feedback on each startup's proposed objectives.

On the morning of each session day, founders meet privately with 4-6 mentors in their track to receive feedback on their proposed objectives. In the afternoon, mentors and founders in each track convene in a classroom (Figure 2) to debate and reconcile individual mentor feedback and finalize a set of three prioritized objectives for each startup to pursue over the next 8 weeks. A

[3] The matching of startups to tracks is centrally administered via the Nobel Prize-winning Gale-Shapley deferred acceptance algorithm. This algorithm uses two-sided preference rankings to produce stable matches. Track leads rank startups and startups rank tracks.

[4] The relative scarcity of angels is consistent with other settings such as SBIR grant competitions (e.g., Howell, 2020).

Figure 1: Sample Startup Dossier

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

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]

Notes: This figure shows a sample startup dossier distributed to mentors before each session. It includes updated objectives, a status update from the CEO, commentary by CDL staff, and the latest financial information. There is also a link to a longer background document with more details on the firm's target customers, core technology, and founders' backgrounds. Portions that may reveal the identity of the startup are redacted.

Figure 2: Finalizing Objectives via a Moderated Debate

Notes: This image shows the discussion moderated by a business school professor (hidden behind the founder) to finalize three objectives for the next 8 weeks.

business school professor moderates these debates. Sessions conclude in the early evening with deliberations, during which mentors declare startups they feel equipped to mentor in achieving their finalized objectives for the following period. Appendix Figure B2 summarizes the day using a sample mentor schedule. See Appendix A for more detail on the quality of objectives and deliberation protocols.

These mentoring decisions are costly as each obligates a mentor to commit four hours of their personal time to helping the startup achieve its objectives. The modal (average) startup receives one (1.61) mentor, and the modal (average) mentor selects one (1.64) startup. Decisions are also high-stakes for startups as those without formal support are dropped from subsequent sessions. CDL managers responsible for each startup connect the founders with the mentor(s) that selected them and facilitate setting up the meetings. They also touch base with founders throughout the 8-week cycle to document progress on objectives and track mentors' honoring of their time commitment. The cycle ends with founders submitting a draft dossier for the next session.

2.2 Mentors & Startups

A mentor is an angel if, from January 2018 to December 2019 (8 months before and 8 months after the study cohort), they made a personal investment. A mentor is a VC if they made a partner investment during the same period. Investment histories are from Pitchbook, Crunchbase, press releases, and CDL's internal records. For each mentor, I also gather a broad range of educational and employment information from public sources such as LinkedIn, Crunchbase, company profiles, SEC filings, and news articles. For employment histories, I record every company at which a mentor

Table 1: Summary Statistics of Mentors

	Angel Investors N = 44		Venture Capitalists N = 148		Difference in Means
	Mean	Standard Deviation	Mean	Standard Deviation	p-value
Experience					
Former Founder	1.00	0.00	0.49	0.50	0.00
Exited Entrepreneur	0.61	0.49	0.32	0.47	0.00
Executive (e.g., CEO)	0.89	0.32	0.94	0.24	0.24
Technical (e.g, data analyst)	0.27	0.45	0.32	0.47	0.52
Academic (e.g., lecturer)	0.05	0.21	0.06	0.24	0.70
Highest Degree					
Bachelor	0.41	0.50	0.30	0.46	0.17
Master (Excl. MBA)	0.14	0.35	0.11	0.32	0.70
PhD	0.23	0.42	0.18	0.39	0.51
Major					
STEM	0.61	0.49	0.50	0.50	0.19
Business (Excl. MBA)	0.14	0.35	0.16	0.36	0.76
MBA	0.16	0.37	0.38	0.49	0.01
Demographic					
Female	0.07	0.25	0.22	0.41	0.03
Age	51.59	11.32	46.28	10.84	0.01
Mentoring					
Mentorship Hours Committed	27.91	16.20	22.73	20.64	0.13
Unique Startups Mentored	4.50	3.09	4.07	3.36	0.45

Notes: This table compares the characteristics of angel and VC mentors.

worked and the positions held. If listed as a founder, I further record whether they exited via an acquisition or IPO. Educational histories include degree levels and majors.

Table 1 describes the 44 angel and 148 VCs in my sample. In terms of both prior founding experience and exit, angels have twice as much operating experience as VCs. However, angels and VCs are similar in terms of managerial, technical, and academic work experience. Educational background is also balanced across majors and highest degrees earned, though VCs are twice more likely to have an MBA degree. Angels are also older and less likely to be female. Lastly, the two are similar in terms of the amount of time they commit to mentoring and the number of distinct startups they choose to mentor.

Table 2 describes the 253 seed-stage companies in my sample. Pre-program information comes from startup applications, first session dossiers, and Internet searches, while post-program funding data are sourced from commercial databases and validated with detailed financing terms sourced directly from founders and mentors.[5] The startups in my sample are predominantly early-stage, high-technology ventures run by young, first-time founders. To assess the representativeness of the sample, I compare its characteristics with those of other U.S.-based high-technology startup samples.

The number of founders (2.6) and employees (4.1) is similar to the 2.6 founders and 3.4 employees found in the sample of seed-stage startups in AngelList (Bernstein *et al.*, 2017), and the 2.9 founders in the MIT E-Lab startups (Hsu, 2007a). Regarding the development stage, 23% have a prototype when applying to the program, which is slightly lower than 29% of university-based projects in the U.S. (Jensen & Thursby, 2001). For IP appropriation strategy, Gans *et al.* (2002) report that funded SBIR ventures give a score of 3.5/5 to the importance of patenting. Following their methodology, I label a binary variable equal to 1 if founders state that they protect their intellectual property by patenting. 71% state they are or will be using patenting as their IP protection strategy, though likely a much lower fraction will file for or be granted a patent–during the 8-month study period, only 13% did.

The median amount of capital raised and revenues generated before joining the program are zero, reflecting the early stage of the startups in my sample. The mean capital raised before joining the program is approximately USD$370 thousand, which is higher than the USD$304 thousand in AngelList startups (Bernstein *et al.*, 2017). Assuming startups were worth close to zero before joining CDL, the four-year step-up in valuation is $10 million, which is much higher than the $2.24 million step-up over eight years in startups that received their first round of VC funding between 2002 and 2010 (Ewens *et al.*, 2018).

Moving to founder characteristics in Panel B, founders are more educated, younger, and less experienced than in comparable samples. Half of the teams have at least one PhD founder, twice the number of startups in MIT E-Lab and MIT Venture Mentoring Services (Scott *et al.*, 2020). The average team age of 34 is lower than the age of 40 found in Ewens *et al.* (2018) and the 2010 Global Entrepreneurship Monitor (Liang *et al.*, 2018), though neither of these samples are

[5] Aggregate equity value created by alumni is the primary performance metric reported by CDL leadership to its board. Thus, special care is taken to ensure funding records are accurate as designated staff leverage their relationship with founders and investors to address inaccuracies, such as missing or incorrect funding amounts and unsuccessful raises that should be excluded from the database.

Table 2: Summary Statistics of Startups

$N = 253$	Mean	Median	Standard Deviation	Min	Max
Panel A: Venture Characteristics					
Founding Team Size	2.55	2	1.22	1	8
Firm Size	4.13	3	5.52	0	50
Has Prototype	0.23	0	0.42	0	1
IPS Patenting	0.71	1	0.46	0	1
Pre-Program Capital ($Million)	0.51	0	1.52	0	20
Pre-Program Revenue ($Million)	0.15	0	0.49	0	5
Post-Program Funding ($Million)	3.80	0	15.90	0	218
Post-Program Valuation ($Million)	10.05	0	37.89	0	507
Panel B: Founder Characteristics					
Num. PhD Founders	1.04	1	1.22	0	5
Has PhD Founder	0.55	1	0.50	0	1
Mean Founder Age	34.40	32	8.77	19	68
Has Founding Exp.	0.41	0	0.49	0	1
Has Startup Work Exp.	0.42	0	0.50	0	1
Has Female Founder	0.26	0	0.44	0	1

Notes: This table describes the characteristics of startups. Financing and revenue amounts are in Canadian dollars.

constrained to seed-stage technology-based companies. In terms of experience, 41% of founding teams have a former founder, slightly less than in Ewens *et al.* (2018). Only 26% have at least one female founder, reflecting the documented underrepresentation of women in tech entrepreneurship (Ruef *et al.*, 2003; Harrison & Mason, 2007).

3 A Novel Typology of Early-Stage Startup Activities

Figure 3 displays the classification system I develop and use to categorize startup objectives. This classification leverages 4,542 business objectives extracted from venture dossiers (the top of Figure 1) to link granular startup activities to the foundations of strategy. Akin to the case study method of Eisenhardt (1989), I develop this model by documenting early firm development in several hundred startups during a seven-year research fellowship at CDL. To implement the classification, I draw on bodies of knowledge in strategy, economics, and finance to define conceptual categories of entrepreneurial activity, then use a replicable labeling procedure to classify business objectives from my setting into these categories. The present work builds on and extends few but notable existing classifications by Carter *et al.* (1996), Reynolds (2000), and Bennett & Chatterji (2023). In Appendix D, I note similarities and differences between my classification and each of these existing efforts.

Conceptual Categories:

Starting with experimentation, I follow an established literature to define it as tests that create real options concerning product, market, and regulation (Levinthal, 2017; Kerr *et al.*, 2014; Manso, 2016).[6] This definition is based on the notion that experimentation is an approach to learning under uncertainty, rather than a trial-and-error method (Ries, 2011; Blank, 2020), or a method of inference (Koning *et al.*, 2022). The classical competitive strategy also highlights learning through analysis, whereby entrepreneurs generate options via search and optimize to a decision (Porter, 1980). This approach underlies such theories as discovery-driven planning (McGrath & MacMillan, 1995), multiple opportunity recognition (Shane, 2000), and search (March, 1991). Following this literature, I define analysis as search and planning activities concerning product, market, and organization (Shane & Delmar, 2004; Delmar & Shane, 2003).[7]

Compared to analysis, experimentation is more costly but also yields more accurate signals (Aghion *et al.*, 1991). Central to this paper, experimentation requires counterfactual thinking, a skill that is developed via learning-by-doing, while analysis conforms to standard practices that can be learned by studying or industry experience. For example, web platforms such as ProductBoard utilize this standardization to offer business planning and product roadmapping services to startups.

The remaining two categories, implementation and resource acquisition, are distinct from the first two in that they are not intended for learning. Implementation refers to the execution of ideas such as sales, marketing, and product delivery, whereas resource acquisition pertains to the appropriation of financial, intellectual, and human capital. Table 3 summarizes the key features of these four conceptual categories, and Figure 4 displays the distribution of each category among startup objectives. Interestingly, the median occurrence of categories in firms' prioritized objectives is roughly equal, indicating the balanced importance of the conceptual categories.

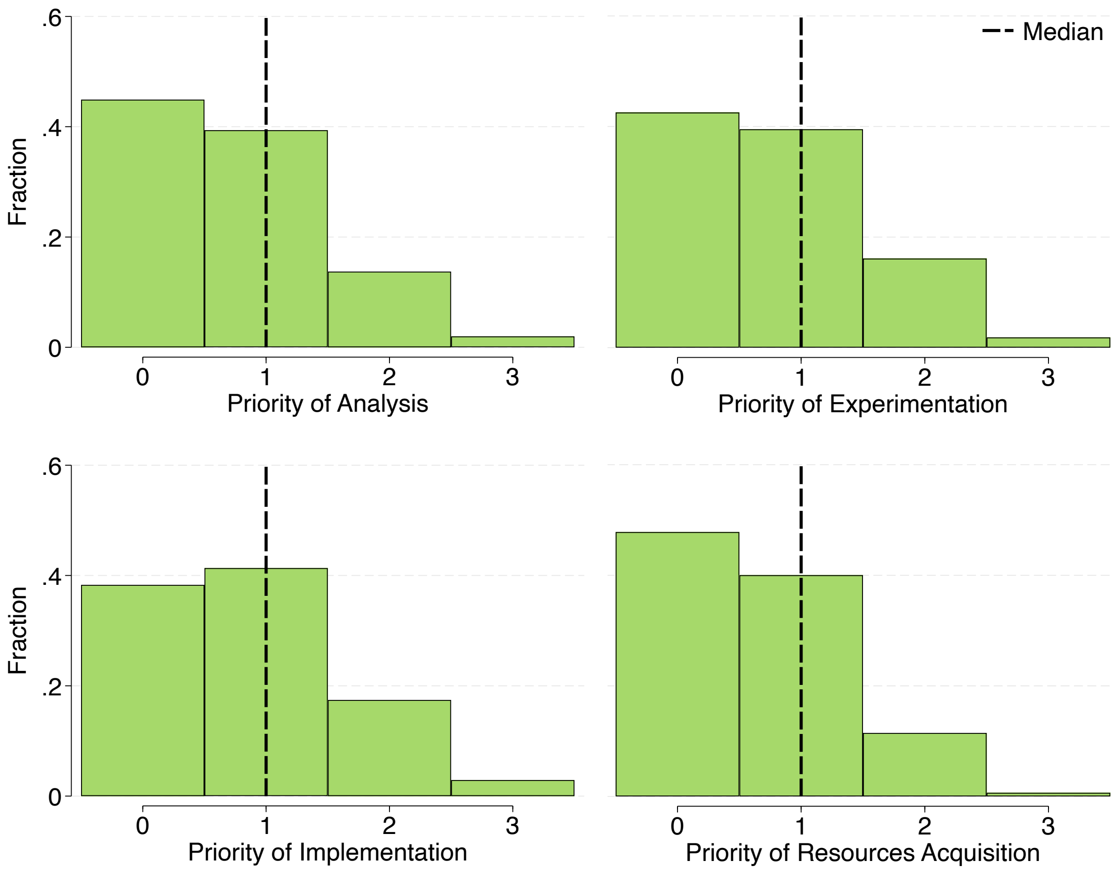
[6] Examples include "validate the accuracy of the machine learning model with new data," "obtain signed letters of intent to purchase," and "compare viable paths to approval by consulting with an investigator."

[7] Examples include "identify ten types of crops with the biggest market in North America," "identify specific beachhead markets," and "prepare capital forecast for next raise."

Figure 3: Typology of Startup Activities

Notes: This figure shows a hierarchical typology of startup activities. The left column called *Activities* is the list of granular business functions obtained after grouping together objectives that are similar to each other. The middle column called *Tasks* is a list of 12 course business tasks that contain related business functions. The right column called *Conceptual Categories* correspond to the four types of startup activity derived from the literature. The connecting lines show the mapping from activities to conceptual categories used to label individual business objectives.

Figure 4: Distribution of Conceptual Categories in Prioritized Objectives



Notes: This figure shows the distribution of conceptual categories in startups' top-three prioritized objectives.

Table 3: Four Conceptual Categories of Entrepreneurial Activity

Category	Features	Examples
Analysis	Low-commitment learning Standard templates Noisier than experimentation	Examine size of the market Develop product roadmap
Experimentation	High-commitment learning No standard template Less noisy than analysis	Validate technology Validate product-market fit
Implementation	Involves selecting ideas Intent is not learning	Launch product Get new customers
Resource Acquisition	Financial capital Human capital Intellectual capital	Raise capital Hire CEO Submit patent application

Notes: This table shows the key features of and stylized examples for each of the conceptual categories.

Labeling Procedure:

Directly labeling thousands of objectives at a conceptual level is prone to cognitive error and would be difficult to reproduce. To overcome these issues, I adopt an iterative clustering approach by first reducing the dimensionality of objectives to a small set of distinct business functions, then mapping these functions to the conceptual categories. The resulting classification is illustrated in Figure 3, with business functions listed in the left column, conceptual categories listed in the right column, and the mapping shown by the connecting lines. The intermediate column shows a set of coarser business tasks that summarize bundles of similar business functions.

In practice, I start by reading objectives in dossiers one at a time and grouping together the ones that are almost identical (e.g., objectives that are about creating a marketing video). Because this step takes place over several months, trying to create mutually exclusive clusters in one pass increases the risk of recency bias. Therefore, I create a new cluster each time I am unsure whether there is an existing cluster for a given activity, resulting in several duplicate clusters. Next, I sort the clusters from the smallest (highest risk of being duplicate) to the largest, and merge those with significant overlap in the core business function (e.g., merge the group for marketing videos with the group on creating marketing brochures). Iterating this process two more times, I arrive at a set of distinct business activities that I cannot reasonably reduce without mixing business functions–these are the 34 activities shown in the left column of Figure 3. Finally, based on the definitions developed earlier, I map each activity to one of the conceptual categories.

For validation, I give three undergraduate students the 34 activity labels and the raw text of the objectives, then ask them to assign one label to each objective based on their understanding of the labels and the content of objectives. The intersection of their labels matches mine in 95% of the cases. In Appendix Table D12, I catalog examples and exclusions for each of the activity classes. To illustrate the iterative labeling procedure, this table shows the 48 activities in the second-last iteration of the merging process, before I reached the final set of 34.

4 Estimation Strategy: Mentoring & Market Performance

This project examines several aspects of advice, including its characteristics and the types of advice provided by different mentors. The estimation approaches for those results are presented within their respective subsections. This section, however, outlines the empirical strategy for estimating the effect of mentoring on startups' market performance.

Outcomes:

The three measures of market performance used are external funding, valuation, and survival as of mid-2023, approximately four years after participating in CDL. Valuation is generally superior to capital raised as it accounts for owners' equity, but it is principally undisclosed and thus remains missing from much of the empirical finance literature. Fortunately, funding information in my data includes financing terms that are sourced directly from founders and investors, enabling me to also use as outcome company valuation at the last funding round.[8] For the main estimates, I transform both funding and valuation into an indicator that equals one if a given startup's amounts are higher than the median funding and valuation among startups in the same technology stream of the program. In supplementary analyses, I also run specifications with these variables in levels. The third outcome is the indicator *Alive* equal to 1 if the firm is still active. This variable accounts

[8] Financing terms can sometimes be missing. In these cases, pre-money valuation is imputed using a 4X multiplier of the amount raised. Thirty of the 253 startups have this 4X multiplier, which means that, at most, 30 startups' valuations are imputed. In Table B1, I show that performance results are robust to excluding these firms.

for the success of positive cash-flow ventures that self-finance operations and do not need to raise capital. To mitigate misclassifying the "walking dead"–nominally active but defunct businesses–as alive, I code the *Alive* variable as zero if LinkedIn profiles show that founders have started new employment.

Estimation:

Regressions are specified as

$$y_i = \alpha + \beta_1 \text{Mentoring}_i + \boldsymbol{x}_i \boldsymbol{\beta}_2 + \gamma_i + \delta_i + \epsilon_i. \tag{1}$$

$Mentoring_i$ is the total hours of mentoring excluding those committed at session one to allow comparison between OLS and IV results. As we will see, I do not have an instrument for the mentoring commitments startups receive at the first session, though I will show supplementary OLS results that include the first session mentoring commitments. $\boldsymbol{x}_i$ is a vector of financial, human, and intellectual capital controls and startup-specific indicators γ_i and δ_i correspond to the site and technology stream in which startups participate.

Instrumental Variable:

The main endogeneity concern is omitted factors that influence both mentoring decisions and firms' market success. To overcome this challenge, I construct an instrumental variable (IV) for mentoring that leverages idiosyncratic conflicts between mentors' personal schedules and the day of CDL sessions. The intuition of this IV is that some mentors are inherently more inclined to support a given startup due to a good expertise fit, but actual mentoring is exogenously hindered by other mentor commitments that conflict with the schedule of CDL's in-person sessions.

The first step in building this IV is to identify the set of good fit mentor-startup matches that are determined by neither founders nor mentors. The set of startup-mentor matches for private meetings that take place in the morning of session days is an excellent proxy. In preparation for the first session, CDL managers determine the founder-mentor match-ups based on their knowledge of each startup's business and each mentor's expertise and preferences. The more of these mentor matches for a given startup happen to attend the second session, the higher the chances of that venture receiving formal time commitment. At the second session, some matches are new, again marking the first time founders meet these mentors privately. Therefore, the instrument for mentoring received at the third session will be equal to the first-session and second-session good matches attending the third session. The instrument is computed analogously for the fourth and final session. To identify matched mentors and mentors attending the sessions, I codify CDL's internal registration records and session-day schedules of each startup and mentor. In some cases, mentors confirm or cancel participation at the last minute, after registration records are closed. To capture these cases, I use the verbatim transcripts of mentoring sessions to validate attendance.

Formally, let $\boldsymbol{M}(t)$ be the binary matrix of session t matches in which cells equal 1 if CDL matched row i startup and column j mentor to meet privately. Then, the set of *new* matches between founders is $\boldsymbol{N}(t) = \boldsymbol{M}(t) \odot \neg \boldsymbol{M}(t-1)$, where $\odot$ is Hadamard (element-wise) product and $\neg$ is the logical not (turns zeros to ones and vice versa), for $t = 2, 3$. Put simply, a cell in $\boldsymbol{N}(t)$ is equal to 1 if row i startup and column j mentor are assigned by CDL to meet for the first time. For the first session $t = 1$, $\boldsymbol{N}(1) = \boldsymbol{M}(1)$. Therefore, the number of each startup's first-time CDL-matched mentors attending each of the subsequent sessions is

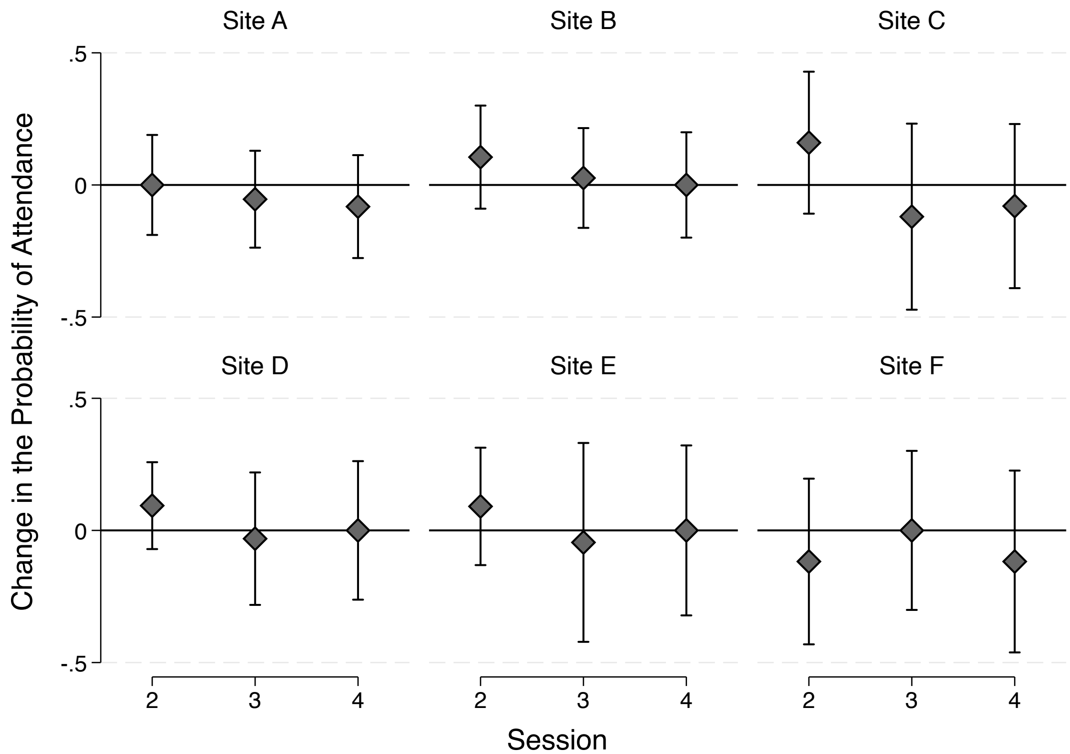
$$\boldsymbol{W}_{I3} = \boldsymbol{N}_{IJ} \times \boldsymbol{A}_{J3}, \qquad \boldsymbol{N}_{IJ} = \sum_{t=1}^{3} \boldsymbol{M}(t) \tag{2}$$

where $\boldsymbol{A}_{J3}$ is the binary matrix of mentor attendance with each cell equal to one if the row j mentor attends the column t session, for $2 \leq t \leq 4$. Then, the instrumental variable z_i at the startup-level is obtained by summing over the count of venture's matched mentors attending sessions that the startup itself was present

$$z_i = w^i_{1\times 3} \times \boldsymbol{S}^i_{3\times 1} \tag{3}$$

where $w^i_{1\times T}$ is the i'th row of $\boldsymbol{W}_{I3}$ and $\boldsymbol{S}^i_{3\times 1}$ is the binary vector of startup's attendance from session two on. In other words, z_i is the number of CDL-matched mentors from previous sessions attending

Figure 5: Within-Mentor Estimated Probability of Attending Sessions



Notes: This graph plots estimates of α_t from the regression $Attending_{jt} = \alpha_t + \beta_j + \epsilon_{jt}$, where α_t denote indicators for sessions with session one as the omitted, and β_j denote mentor fixed effects and standard errors clustered by mentor. Alternative specifications without mentor fixed effects or without clustered standard errors result in larger confidence intervals, no change in overall patterns, and no instance of 95% CI falling outside of zero.

future sessions of the startup.

Exclusion Restriction:

The validity of the exclusion restriction rests upon the assumption that mentors' personal schedules are not related to the quality of startups, except through the mentoring support they can provide. This is a reasonable assumption given that CDL mentors manage demanding professional schedules that preclude them from attending all sessions. I am also not aware of any restrictions or incentives that motivate mentors to attend a particular session. This is visible in Figure 5 depicting within-mentor estimates of the probability of attending sessions by site. There are no discernible patterns.

The fact that startups that receive no mentor commitments are dropped from subsequent sessions poses a threat to the validity of the exclusion restriction. Consider a startup that is dropped at the third session, despite having a matched mentor present, perhaps due to a new negative signal revealed (e.g., a failed technical validation experiment).[9] This causes the IV for that venture to stop changing for subsequent sessions, thus allowing venture survival in the program to open a path between firm quality and the instrument, violating the exclusion restriction.

Since the issue is the possibility that unobserved quality encoded in CDL survival outcomes affect the value of the IV, this path can be blocked by running regressions in samples conditioned on startups *present* at each of the second, third, and fourth sessions, with the endogenous variable equal to mentoring received at that session only, and the instrument equal to the matched mentors of the startup attending that session. In this construct, whether or not a given venture is dropped has no bearing on the value of the IV.

5 The Effect of Mentoring on Market Performance

Table 4 shows the relationship between mentoring and three market measures of performance. For each dependent variable, I report baseline results, but for conciseness I will focus on estimates with the full set of controls. Columns 4-2 and 4-4 show that an extra hour of mentoring is associated with a 1.3 percentage point, or 3% increase, in the probability of achieving above-median external funding and valuation within four years of having participated in CDL. Column 4-6 shows that an additional hour of mentoring is associated with 0.58% increase in the probability of survival. Appendix Table B1 shows that these results are robust to running regressions session by session, and to nonlinear estimates with dependent variables equal to funding and valuation in levels.

IV Estimates:

Table 5 presents the 2SLS estimates of the relationship between mentoring and market performance. Column 5-1 shows the first-stage results and the test of weak instruments. An extra matched mentor attending a future session is associated with 0.8 more mentoring hours committed, a 20% increase

[9] This should not happen because, by design, CDL instructs mentors to base their mentoring decisions on their ability to help the startup achieve its objectives, not perceived quality. The purpose of the cutting mechanism is to progressively focus mentoring resources on startups that at least one participating mentor finds capable of supporting. Furthermore, clearly low-quality startups (e.g., untruthful founders), if they pass through CDL's admission process, will most likely get cut at the first session, thus posing no threat to IV validity. Nonetheless, I cannot strictly rule out the possibility that mentors take quality into account in their mentoring decisions.

Table 4: The Effect of Mentorship on External Funding, Valuation, and Survival: OLS Estimates

Dependent Variable:	AbvMed Funding		AbvMed Valuation		Alive	
	4-1	4-2	4-3	4-4	4-5	4-6
Mentoring Hours	0.012***	0.013***	0.012***	0.013***	0.005***	0.005**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Pre-Program Capital ($Million)		0.012		0.012		0.005
		(0.021)		(0.021)		(0.007)
Pre-Program Revenue ($Million)		−0.028		−0.029		0.033
		(0.042)		(0.042)		(0.021)
Has Prototype		−0.086		−0.082		0.012
		(0.083)		(0.083)		(0.062)
Firm Size		−0.008		−0.007		0.007**
		(0.005)		(0.005)		(0.003)
Share PhD Founder		−0.117		−0.099		0.030
		(0.100)		(0.100)		(0.074)
Share Business Degree		0.110		0.092		0.091*
		(0.113)		(0.112)		(0.054)
Share Ex-Founder		0.151		0.156		−0.004
		(0.107)		(0.106)		(0.069)
Share Industry Exp.		0.120		0.119		0.125*
		(0.103)		(0.103)		(0.076)
Mean Founder Age		0.018		0.014		0.037*
		(0.019)		(0.019)		(0.020)
Mean Founder Age^2		−0.000		−0.000		−0.000**
		(0.000)		(0.000)		(0.000)
IPS Patenting		0.093		0.091		−0.022
		(0.075)		(0.075)		(0.056)
Mean of DV		0.431		0.431		0.866
N	253	253	253	253	253	253
R^2	0.10	0.17	0.09	0.16	0.04	0.13
Site FE		Yes		Yes		Yes
Stream FE		Yes		Yes		Yes

Notes: This table shows the OLS estimates of the relationship between mentoring and startup performance. Dependent variables are indicated in column headers. *Mentoring Hours* is the total hours mentors committed to the startups from the second session onwards. Robust standard errors in parentheses. Statistical significance is denoted by *(10%), **(5%), or ***(1%).

Table 5: The Effect of Mentorship on External Funding, Valuation, and Survival: IV Estimates

	First Stage	Second Stage		
	5-1	5-2	5-3	5-4
Dependent Variable:	Mentoring Hours	AbvMed Funding	AbvMed Valuation	Alive
Mentoring Hours		0.016***	0.016***	0.008***
		(0.003)	(0.003)	(0.003)
Matched Mentors Attending	0.848***			
	(0.040)			
F-statistic	450			
FEs & Controls	Yes	Yes	Yes	Yes
N	253	253	253	253

Notes: This table shows the 2SLS estimates of the relationship between mentoring and startup performance. Dependent variables are indicated in column headers. *Mentoring Hours* is the total hours mentors committed to the startups from the second session onwards. Robust standard errors in parentheses. Statistical significance is denoted by *(10%), **(5%), or ***(1%).

in the probability that an additional mentor commits to provide mentoring advice over the next 8-week period. The effective first-stage F-statistic of 450 rules out the null that instrument is weak.[10] All second-stage results in Columns 5-2 to 5-4 have the same sign as and are similar in magnitude to the corresponding OLS results. The slight increase in magnitude could be due to the local nature of the effects. The IV estimates reflect the causal effect of mentoring on success for startups affected by mentors' idiosyncratic schedule conflicts, presumably startups that may experience a higher marginal benefit from mentoring.

As noted earlier, the CDL program's design to drop startups that receive no mentoring at a given session poses a threat to the exclusion restriction by opening a direct path between market success and the instrumental variable. Running IV estimates session-by-session forecloses this path since the disaggregated value of the IV for a given session is not affected by whether or not the startup gets dropped at that session. Appendix Table B2 displays these estimates with above-median funding as dependent variable. Results with above-median valuation as dependent variable are similar. Overall, estimates are consistent with the full-sample results with two notes. First, while by-session IVs are still strong, they are relatively weaker than the aggregate version used in the full sample. Second, subsample 2SLS coefficients are larger than those from the full sample estimates because the same value of market success is regressed on the smaller set of mentoring hours committed at

[10] The effective F-statistic is calculated by multiplying the Cragg-Donald Wald F by a correction factor to account for heteroskedasticity (see Olea & Pflueger, 2013).

one session.

These findings establish a large and significant causal link between mentoring and the market performance of startups, but they do not speak to the mechanisms underlying this effect. By characterizing the nature of advice and its provision by different types of mentors, the rest of this paper provides clues about the mechanisms that may drive these results.

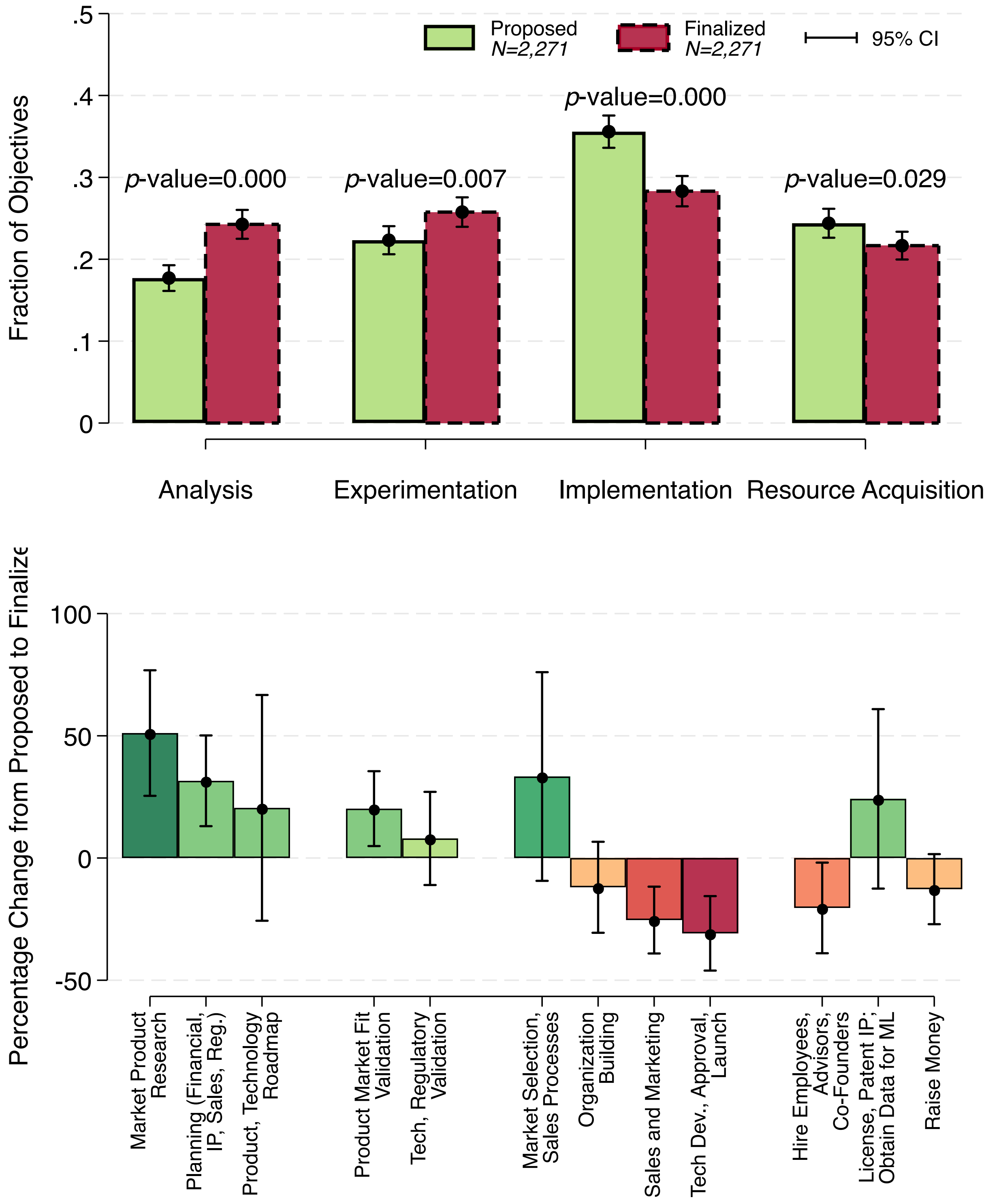
6 The Nature and Provision of Advice

The classification immediately reveals an important fact about the nature of advice. The top portion of Figure 6 shows the fraction of objectives in each conceptual category by whether objectives are from the set founders proposed before the mentoring sessions, or from the set finalized at the end of the session day. Relative to mentors, founders significantly under-prioritize both analysis and experimentation for more implementation and resource acquisition. Viewing analysis and experimentation as purposeful learning–that is, activities intended for generating information, mentors seem to encourage entrepreneurs to do less and learn more.

The bottom panel of Figure 6 reveals more granular insights by depicting changes in the share of tasks within each conceptual category from proposed to finalized. Founders increase the priority of *all* analysis and experimentation tasks. The largest increase of 50% is in *Market Product Research*, followed by a 30% increase in *Business Planning* activities. The increase in the share of experimentation is also large, with *Product Market Fit Validation* activities receiving a 14% boost in priority. Conversely, founders walk back 25% of *Sales and Marketing* and 30% of *Tech Development, Approval, and Launch*, the two primary market and product implementation tasks. Resource acquisition tasks are also reduced, with hiring receiving the largest drop.

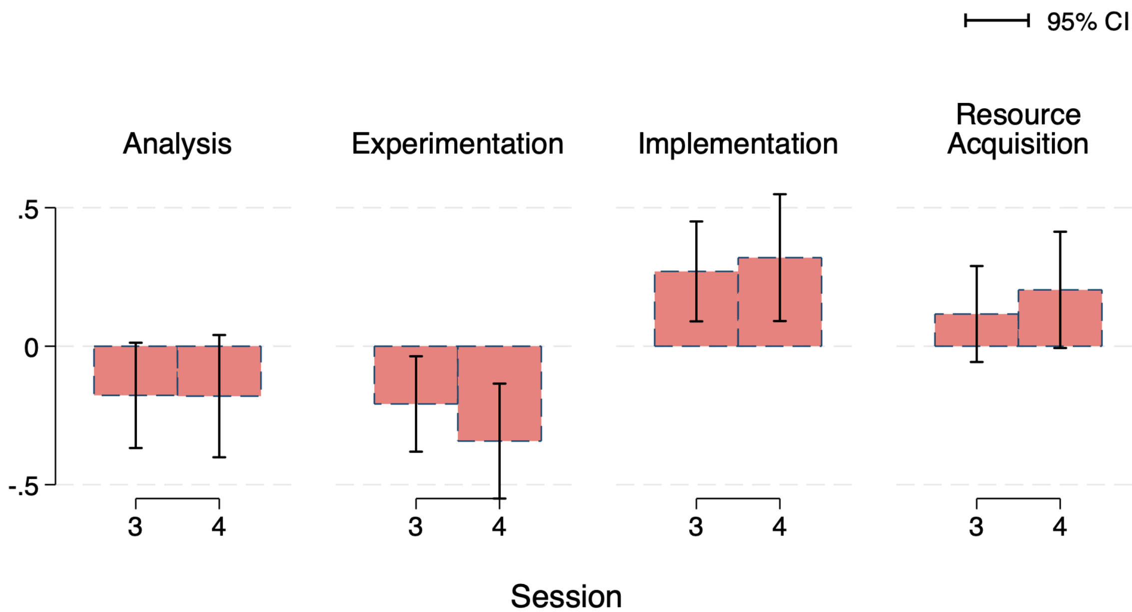
An interpretation of these results is that mentors nudge entrepreneurs away from activities that entail significant commitments. Even among learning activities, the largest increases occur in low-commitment and noisy approaches, such as search and planning. Conversely, the largest decreases are in tasks requiring significant commitments to specific product market ideas. A more magnified view in Appendix Table D13 shows that the only product-market implementation activity *not* reduced is *Obtain Regulatory Approval*, which itself can be thought as an exercise in validating product feasibility. There is also a large, though insignificant, increase in *Market Selection, Sales*

Figure 6: Differences between Proposed and Finalized Objectives



Notes: The top figure shows the average fraction of objectives in each conceptual category in proposed and finalized objectives. The p-values correspond to t-tests of differences in shares between proposed and finalized objectives. The bottom figure shows the percentage change in the fraction of tasks from proposed to finalized. Bar colors range from dark green (highest increase) to dark red (highest decrease). The error bars display 95% confidence intervals of the t-test that differences are significantly different from zero.

Figure 7: Changes in Objectives after Completing Analysis and Experimentation



Notes: Each subgraph plots the estimated coefficients of interactions between session indicators and the number of analysis and experimentation objectives completed in the previous session, with dependent variable equal to the priority of the activity in the subgraph title in the finalized objectives of the focal session. The omitted category is session two. Session one observations are dropped due to missing lagged objectives. Regressions include venture fixed effects and standard errors are clustered by startup.

Processes. This may seem to contradict the view that mentors advise founders to do less, but it is consistent with the idea that mentors guide founders away from making strong early commitments. Sales processes can be agnostic to some variations in product and market, and market selection may include some search and evaluation efforts.

If mentors encourage entrepreneurs to learn more in order to discover and test options before making a choice, then we should observe that learning to be associated with a shift of priorities towards implementation and resource acquisition in future sessions. Figure 7 provides a visual inspection. This graph shows within-venture estimates from regressing the priority of each activity type at a given session on the number of analysis and experimentation objectives completed in the previous session. A clear pattern emerges: past completion of analysis and experimentation activities leads to a shift of priorities towards implementation and resource acquisition.

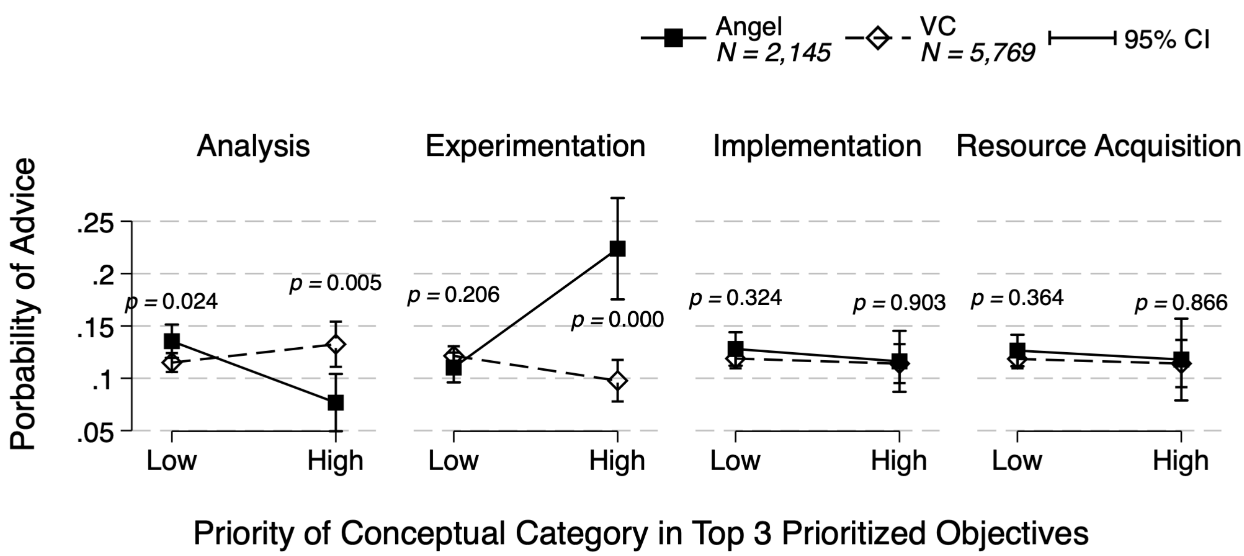
6.1 The Provision of Advice: Angels versus VCs

A key question prompted by these results is that, beyond their verbal feedback during the session days to revise proposed objectives, which types of mentors meaningfully aid founders in accomplishing their finalized objective. I address this question by distinguishing between angel and VC mentors, motivated by the significance of this distinction in strategy and finance literatures. Comparing the non-financial benefits of angels and VCs sits at the intersection of entrepreneurial finance and strategy. Investors spur innovation and economic growth by financing risky ideas (Kortum & Lerner, 2000; Samila & Sorenson, 2011), but also vary significantly in their ability to grow startups (Sorensen, 2007). Understanding how angels and VCs–two structurally distinct but competing sources of capital–differ in supporting nascent entrepreneurs offers clues about the sources of the observed heterogeneity in investor value-added (Da Rin *et al.*, 2013). Such insights would then concern entrepreneurial strategy as investors are business partners who are quite challenging to obtain and nearly impossible to lose.

Figure 8 plots the probability of angels versus VCs choosing to help startups achieve their finalized objectives under different task regimes. The largest wedge in mentoring preferences is on experimentation advice. When experimentation is not the top business priority (zero or one of the three objectives are experiments), angels and VCs are roughly equally likely to choose to provide advice, but when it is the top business priority, the probability of angels choosing to provide advice doubles from 0.11 to 0.22. Alternatively, Appendix Table B3 shows that the share of experimentation objectives in top-three priorities is 26% higher among angel-mentored startups than among VC-mentored ones. Figure 8 also shows that VCs are instead more likely than angels to provide advice on analysis, while the remaining panels show no difference in terms of implementation and resource acquisition activities.

As previously noted, the academic literature broadly agrees that experimentation is central to the entrepreneurial process, but increasingly, scholars have also warned against the unintended consequences of reckless experimenting. As the first step in unpacking the experimentation results, I tackle the main endogeneity concerns with more sophisticated multivariate methods. Chief among these concerns is that the univariate tests so far do not account for the unobserved qualities of startups and mentors.

Figure 8: The Probability of Angel versus VC Advice by Activity Type Supported



Notes: This graph shows the probability that angels and VCs commit four hours of their personal time to advise startups on achieving the business objectives prioritized for the next 8 weeks. In the Analysis panel, Low means none or one of the top three objectives are analyses, and High means that two or three of the startup's top three objectives for the next 8 weeks are analyses. High and Low are analogously defined for the remaining panels. Each panel shows p-values for differences in means tests of the probability of angels vs VCs committing their time to advise startups on how to achieve their prioritized objectives.

Estimation Strategy:

The desired statistical approach compares angels' and VCs' likelihood of providing different types of advice by constructing each mentor's bundle of startup choices from which they can choose. Therefore, I codify accurate scheduling information that shows each mentor's attendance in the group meeting of each track at each session. Appendix Table B4 illustrates this structure with sample data. Thus, the estimation specification is

$$Advice_{ijt} = \beta_1 Angel_i \times Experiment_{jt} + \beta_2 Experiment_{jt} + \boldsymbol{x}_{jt}\boldsymbol{\beta}_3 + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt} \tag{4}$$

where $Advice_{ijt}$ is an indicator that equals 1 if mentor i chooses to advise startup j on achieving its session t objectives, $Angel_i$ is an indicator that equals 1 if mentor i is an angel and zero if a VC, and $Experiment_{jt}$ is an indicator that equals 1 if the majority–two or three–of startup j's three prioritized objectives at session t are to experiment. The mentor and startup fixed effects, denoted by γ_i and δ_j, account for the unobserved qualities of startups and mentors. Session fixed effects denoted by η_t allows for comparing objectives initiated during the same period.

Fixed effects remove some of the major concerns, but changes in the growth potential of startups may also confound the mentoring decisions of active investors. To alleviate this concern, I add a vector of time-varying financial controls $\boldsymbol{x}_{jt}$ that summarizes each startup's growth trajectory. These controls are $RevenuePositive_{jt}$, which equals 1 if the startup is revenue-positive to account for investor risk preferences, $AbvMedFunding_{jt}$, which equals 1 if total funding is above-median to account for round size preferences, and $OpenRound_{jt}$, which equals 1 if the startup is raising capital to account for deal flow incentives. The equation is estimated as a linear probability model (LPM) with mentor clustered standard errors to account for error correlation in mentors' decisions.[11] The coefficient of interest β_1 shows the difference in the probability of receiving experimentation advice from an angel instead of a VC.

[11] Although the response variable is binary, I use LPM because nonlinear models such as logistic produce inconsistent estimates with multi-way fixed effects due to the incidental parameter problem (Kwak *et al.*, 2023). The issue is less severe when there are many observations for each effect (e.g., several startup-mentor observations for each session FE), and more severe when there are few observations for each effect (e.g., a handful of mentor-session observations for each venture FE). It is possible, however, to use a class of models called fixed effects logits with one set of fixed effects, which I do to report supplemental results.

Table 6: Provision of Experimentation Advice by Angels and VCs

DV = Advice	(6-1)	(6-2)	(6-3)	(6-4)	(6-5)	(6-6)
Angel	0.008	0.008	–0.011			
	(0.010)	(0.009)	(0.010)			
Experimentation	0.011	–0.007	–0.042***	–0.043***	–0.044***	–0.044***
	(0.012)	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)
Angel × Experimentation			0.136***	0.145***	0.144***	0.144***
			(0.027)	(0.028)	(0.028)	(0.028)
Revenue Positive						–0.016
						(0.017)
AbvMed Funding						0.006
						(0.018)
Open Round						0.009
						(0.013)
N	7,914	7,914	7,914	7,914	7,914	7,914
Mean of DV						0.120
Startup FE		X	X	X	X	X
Mentor FE				X	X	X
Session FE					X	X

Notes: This table shows the relationship between investor type and the provision of experimentation advice. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

Estimates:

Table 6 shows OLS estimates of Equation (4). Columns 6-1 and 6-2 show that angels and VCs are indistinguishable in their willingness to provide advice. There is also no evidence that being in an experimentation phase is predictive of receiving mentoring support. Columns 6-3 to 6-6 contain the main interaction term with progressively demanding controls. The fully specified estimates in Column 6-6 shows that the interaction effect for *Angel* × *Experimentation* is large and significant. In terms of magnitude, angels are 14.4 percentage points–over twice–more likely than VCs to provide experimentation advice.

A key concern here is that this result is an artifact of the way in which objectives are classified. For example, business planning, a pervasive task I categorize as analysis, may be predicated on product market experiments, such as surveying potential customers. This raises the question of whether a more flexible definition of experimentation might alter the results. To investigate, I create two broader definitions of experimentation by rearranging the links between Activities and Conceptual Categories in Figure 3. In the "low-broad" alternative, I add *{Develop Business Plan:* a_6*}* to the experimentation category. In the "high-broad" alternative, I also add *{Choose Market:*

$a_{18}\}$, because the unobserved context of selecting a target market may also involve validation experiments. Results in Appendix Table B5 show that the main finding is robust to these alternative measures. This table includes further tests against alternative specifications of measuring the priority of experimentation as well as changes in the estimation model.

It is worth emphasizing that the comparative estimates so far should not be taken to mean that VCs comparatively lack ability to drive entrepreneurial learning. Learning and choice also occur via analysis, which is the approach VCs are comparatively more likely to support. Table B6 shows this in multivariate estimates, but later in Section 8, I build on these results to further explore VCs' skill advantages.

6.2 Mechanism: Learning-by-Doing

Why are angels more likely to help startups run experiments? This section offers two sets of evidence supporting the hypothesis that experimentation is a skill developed via learning-by-doing, and angels have a skill advantage in that domain due to having more operating experience than VCs. First, I show that the experimentation effect is driven by angels who have substantial operating experience. Second, I find that the experience mechanism is only salient in supporting less experienced founding teams. In the next section, I also show that the experience mechanism becomes even more salient when mentors' relative skills are estimated using the quality of their advice.

Mentor Operating Experience:

To capture mentors' experience, I use exit as a clear market-based threshold of substantive operating experience.[12] A mentor is exited if the company they founded was acquired or was taken public. Of course, not all acquisitions are financially successful. This is not an issue, however, because the phenomenon of interest here is not success, but meaningful entrepreneurial experience. Notwithstanding, exit likely underestimates experience for operators who fall just below this

[12] One may be inclined to use founding experience instead of exit. However, founding history is not appropriate for capturing one's extent of operating experience. The founder of a boutique consulting firm acquires different skills than the founder of a scalable startup, and the latter has less experience than a founder who grows their firm to a mature stage. To the extent exit sets a lower bound for entrepreneurial involvements, it proxies for meaningful operating experience more accurately than one's claim to have founded a company.

Table 7: Operating Experience and Provision of Experimentation Advice

	Sample of Angel Decisions		Sample of VC Decisions	
DV = Advice	(7-1)	(7–2)	(7–3)	(7–4)
Exit:	Yes	No	Yes	No
Experimentation	0.095**	0.052	–0.043	–0.034*
	(0.042)	(0.044)	(0.028)	(0.020)
N	1,158	908	2,056	3,698
FEs & Controls	X	X	X	X

Notes: This table shows the likelihood of providing experimentation advice in sub-samples of angels and VCs split by exit history. Controls and fixed effects used are identical to the main specification in Column 6-6 of Table 6. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

threshold.

Table 7 shows the change in the probability of receiving experimentation advice in samples conditioned by experience and investor type. Comparing Columns 7-1 and 7-2 shows that only exited angels are significantly more likely to provide advice on experiments than on other activity types. The magnitude of the coefficient is also larger for the exited angels than any other investor type. Columns 7-3 and 7-4 further indicate an overall lack of interest in mentoring experiments by VCs. It is puzzling that we do not see a positive experience effect for exited VCs similar to the positive effect for angels. One explanation is that the measurement error in exit–that it underestimates experience–is more severe for VCs. For example, individuals who fall just below the exit threshold may be more likely to become a VC because they do not acquire the personal wealth needed for angel investing.

Founder Operating Experience:

If experimentation skills are developed via learning-by-doing, then less experienced founding teams should be more likely to receive advice from experienced mentors than from inexperienced ones. In my data, 41% of the founding teams have an ex-founder, and 42% have a founder who has worked for a startup. I leverage these variations to estimate regressions of the form

$$
\begin{aligned}
Advice_{ijt} = {} & \beta_1(Experiment_{jt} \times MentorExpr_i \times TeamExpr_j) \\
& + \beta_2(Experiment_{jt} \times MentorExpr_i) + \beta_3(Experiment_{jt} \times TeamExpr_j) \\
& + \beta_4(MentorExpr_i \times TeamExpr_j) + \beta_5 Experiment_{jt} \\
& + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt}
\end{aligned} \tag{5}
$$

where $MentorExpr_i$ and $TeamExpr_j$ are indicators for mentor and founding team experience.

Figure 9 visualizes the results. The two left graphs measure mentor experience using exit; the right graphs measure it as prior founding history. The top two graphs measure team experience as prior founding history; the bottom graphs measure it as startup work experience. The top estimates in each subgraph show whether experienced mentors provide more experimentation advice than inexperienced mentors to teams without any startup experience (β_2), and the bottom estimates show this for teams with startup background ($\beta_1 + \beta_2$).

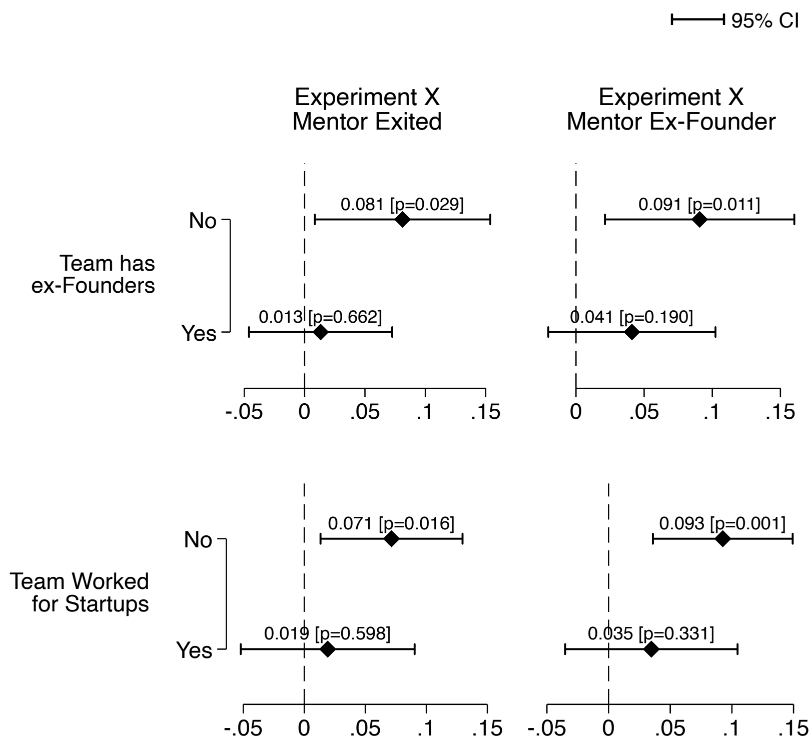
Across the board, experienced mentors provide more experimentation advice, but only to inexperienced teams. Appendix Figure B3 shows that this result does not hold for other activity types, meaning that the experimentation effect is not driven by general substitutions in the human capital stocks of mentors and mentees, thus further supporting the learning-by-doing mechanism.

6.3 Quality of Experimentation Advice

If experience drives experimentation skills, it should also lead to more effective advice. To measure the quality of advice, I use accurate information on whether the startup achieved each of its objectives.[13] Completion is an appropriate measure of advice quality for two reasons. As Hellmann & Puri (2002) show, advancing firm development is a primary function of investors–the firm must execute for investors to make returns. Timely execution is also a benefit founders seek in "smart money" to unlock additional resources. If the session-day feedback given by experts approximates the true startup priorities better than those initially proposed by mostly inexperienced founders, then variation in the completion of prioritized tasks contains information about the

[13] CDL managers are responsible for verifying evidence of completion before releasing dossiers to mentors. Also, founders have strong incentives to be truthful because both CDL managers and current mentors are aware of actual progress on objectives and would detect false claims during sessions.

Figure 9: Heterogeneity of Experimentation Advice by Founder and Mentor Experience



Notes: This figure plots estimates from Equation (5). The top estimate in each subgraph is for β_2: the marginal difference in providing experimentation advice by experienced mentors to inexperienced founding teams. The bottom estimate in each subgraph is for $\beta_1 + \beta_2$: the marginal difference in providing experimentation advice by experienced mentors to experienced founding teams. The p-values for the significance of each estimate is also reported.

effectiveness of advice.

A challenge of using completion to detect advice quality is that tasks are heterogeneous in difficulty. For instance, consider preparing a hiring plan, which is likely much less challenging than hiring an employee. The same task also has cross-startup variability in difficulty. For example, it is much harder to obtain regulatory validation (relative to other tasks) for therapeutics than for medical devices. These sources of heterogeneity can grossly obscure any skill effects because a mentor's advantage in a given domain likely correlates with selecting on more specialized, less obvious tasks in that domain. To absorb this heterogeneity in task difficulty, I use task-startup fixed effects, in addition to the existing mentor and session fixed effects. Specifically, I estimate

$$Completion_{ijst} = \beta_1 Angel_i \times Experiment_{jst} + \beta_2 Experience_i \times Experiment_{jst} + \gamma_i + \delta_{js} + \eta_t + \epsilon_{ijst} \tag{6}$$

where the new subscript s denotes objectives and δ_{js} denotes startup-task fixed effects.

Table 8 reports the results. The first three columns show that only prior operating experience is significantly associated with completing experiments. Also, as expected, angel-mentored startups are more likely to complete their experiments than VC-mentored startups, though the estimates are not distinguishable from zero. This is not surprising if capturing execution success requires a more precise measure of skills, in this case encoded in exit rather than just being an angel.

These results are vulnerable to three major endogeneity concerns. First, being a former entrepreneur may drive one's choice to become an angel investor rather than a venture capitalist.[14] Thus, the skill estimates would be biased if angels and VCs follow different career paths and these paths shape their business skills differently. Second, it may be one's broader industry experience, rather than operating experience per se, that drives experimentation skills. Third, the results may be driven by mentors' homophilous choice, which is problematic when determinants such as gender and race influence exposure to entrepreneurial opportunities. To address these issues, I conduct

[14] Not all angel investors are former entrepreneurs. A notable exception is individuals who invest family wealth, although usually professional wealth managers make these investments. This paper focuses on angels who compete with VCs in funding and advising early-stage companies. Due to the highly risky nature of startup investing, these angels must possess significant personal wealth, typically only attainable via entrepreneurial profits. Similarly, my results do not pertain to individuals who invest in small increments through crowdfunding campaigns or syndication platforms.

Table 8: Quality of Experimentation Advice

DV:	Completition			Immediate Drop or Graduation	
	(8–1)	(8–2)	(8–3)	(8–4)	(8–5)
Sample:	Full	Full	Full	Session 1	Session 1 & Experimenting
Angel × Experimentation	0.030		0.024		
	(0.029)		(0.032)		
Experienced × Experimentation		0.041**	0.037**		
		(0.015)	(0.017)		
Completed Objectives in:					
Analysis				−0.012	−0.047
				(0.077)	(0.108)
Experimentation				0.098*	0.106**
				(0.038)	(0.036)
Implementation				0.056	0.211
				(0.136)	(0.188)
Resource Acquisition				0.030	0.012
				(0.068)	(0.078)
N	2,393		2,393	209	120
Mean of DV			0.565	0.670	0.683
Mentor FE	X	X	X		
Session FE	X	X	X		
Startup × Task FE	X	X	X		
Stream FE				X	X
Site FE				X	X

Notes: This table shows results for the quality of experimentation advice. The first three columns regress completion status of objectives on investor type and operating experience, with two-way standard errors clustered by mentor and task reported in parentheses. Data is at the startup-session-objective-mentor and the sample is conditioned on advice. The remaining two columns show the correlation between completing different objectives and success, where success is defined as either immediate shutdown, measured by being dropped from the program at session 2, or graduating from the program by surviving all four sessions conditional on not being dropped at session 2. All models control for the number of objectives attempted in each of the four conceptual categories. 44 startups who attended their first in-person meeting at session 2 or later are dropped. Standard errors clustered by site are in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

a series of tests in Appendix C. For the first problem, I employ inverse probability of treatment weighting (IPTW) to attenuate bias. For the second problem, I re-estimate Equation (6) using three alternative measures of industry experience. For the third problem, I examine several dimensions of homophilous choice. All results support the hypothesis that it is operating experience that drives mentors' experimentation skills.

Predictiveness of Completion:

How relevant is completing experiments to reducing information asymmetry? A natural test of relevance is whether completing experiments is predictive of investors' improved beliefs about startup quality. To measure belief precision, I code an indicator that equals 1 if the startup is dropped at the second session, when the results of the first-session mentoring and objectives are observed (i.e., immediate shutdown) or conditional on surviving the second session, if the startup never gets dropped.[15] Put differently, mentor beliefs would be less precise if, after 8 weeks of mentoring the startup and observing the outcomes of attempting high-priority objectives, they believe that the firm is good enough to continue receiving costly mentoring resources, but later change their minds and drop the startup from the program anyway. The statistical approach then regresses this outcome on the types of activity attempted and completed since the first session.

The remaining two columns of Table 8 report the results. Column 8-4 shows that, after the first session, completing experiments predicts improved investor beliefs, but this is not the case for analysis, implementation, and resource acquisition. It is possible that startups that do not prioritize experimentation in the first session are more advanced, thus mentors drop them in an intermediate step not because of quality concerns, but because the specific needs of the startup, such as help with fundraising, are satisfied. In column 8-5, I condition the sample on startups that prioritize experimentation in the first session. Results are similar, with a slight increase in size and statistical significance. In terms of magnitude, completing an extra experiment is associated with an approximately 15% increase in the precision of investor beliefs. In other words, experiments appear to reveal more useful quality signals than any other activity type.

This finding is closely related to the scientific approach to decision-making (Camuffo *et al.*,

[15] Using immediate shutdown as a measure of improved beliefs entails a false negative error–good startups that should not have been dropped. However, the magnitude of this error does not appear large. Only 7% of these startups ever raise capital, compared to the sample average of 45%.

2020). This work shows that a methodical approach to hypothesis generation and testing increases the rate of early abandonment, a result that has since been replicated and extended (see Camuffo *et al.*, 2024; Novelli & Spina, 2024).

7 Alternative Explanations

Since random assignment of mentors and advice is infeasible, I use different econometric techniques to alleviate the major endogeneity concerns. These techniques, however, do not rule out important alternative explanations. In this section, I identify and examine four of main alternative explanations: 1) deal flow incentives, 2) stage preferences, 3) sorting, and 4) information preferences. Table 9 summarizes the primary tests for each alternative explanation, while Appendix Table B7 provides supplemental tests with additional measures.

Deal flow incentives:

The most salient alternative explanation is due to financial incentives. By mentoring, investors obtain quality signals that mitigate information asymmetry with investment targets. This is an issue if the intensity of financial incentives differs systematically between angels and VCs in a way that coincides with the type of objectives startups prioritize. For example, VCs may have more substantial incentives to prioritize deal flow as their compensation is tightly linked to committing their capital before it expires (Barrot, 2017). At the same time, startups close to funding may be less likely to be in an experimentation phase.

To evaluate this explanation, I exploit variation in the capital requirements of startups. Table 9 Columns 9-1 and 9-2 run the main specification in sub-samples of startups split by having an open round. The stability of the coefficient of interest indicates that even this sharp change in exposure to deal flow does not change the main result. A concern with this test is that the influence of deal flow incentives affects behavior before rounds open since investors can anticipate the need to raise in the future. In supplemental tests shown in Appendix Table B7, I find that the results are also robust to expected funding by running results in samples split by median runway. Runway is a metric that uses cash flow and cash burn rate to calculate time remaining before the firm needs to raise capital again.

Table 9: Tests of Alternative Explanations

Explanation: DV =	Deal Flow Incentives Advice		Stage Preferences Advice		Sorting Advice		Information Preferences Advised Experiments	
Sample:	(9-1) No Open Round	(9-2) Open Round	(9-3) BlwMed Funding	(9-4) AbvMed Funding	(9-5) Full Sample	(9-6) Full Sample	(9-7) Feedback Sample	(9-8) Feedback Sample
Angel × Experimentation	0.128***	0.115***	0.129***	0.171***	0.116***	0.102***		
	(0.032)	(0.040)	(0.036)	(0.049)	(0.028)	(0.032)		
Matched					0.351***	0.356***		
					(0.028)	(0.029)		
Angel × Matched					0.065	0.043		
					(0.056)	(0.059)		
Matched × Experimentation						−0.026		
						(0.068)		
Angel × Matched × Experimentation						0.109		
						(0.105)		
Angel							−0.021	−0.066
							(0.064)	(0.068)
Proposed Experiments							0.566***	0.538***
							(0.062)	(0.058)
Angel × Proposed Experiments								0.077
								(0.096)
N	3,899	4,015	4,413	3,501	7,914	7,914	411	411
Startup FE	X	X	X	X	X	X	X	X
Mentor FE	X	X	X	X	X	X		
Session FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X

Notes: This table shows tests of four alternative explanations based on deal flow incentives, stage preferences, sorting, and information preferences. Columns 9-7 and 9-8 use the sample of private meetings in the morning of session days. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

These results may appear surprising: how can investors *not* take advantage of mentoring to compete for better deals? They likely do, but not by strategically selecting on higher quality startups to mentor. First, investors vary in their evaluation ability, thus mentoring based on expertise reveals more information in a setting where signals disseminate quickly. Second, there are reputational costs as other investors can detect strategic behavior. Third, investors cannot strategically select on startup quality to exclude others from investing because startups can have more than one mentor. Fourth, even with sufficient incentives to collude with fellow mentors, founders and CDL managers also reveal information, making it rather challenging for a given mentor to bury private information. In Appendix A, I provide a more extensive discussion on this matter.

Stage preferences:

VCs have a higher presence than angels in late-stage funding. If experimentation is less frequent in later stages, one may worry that the main result is an artifact of VCs' stage preferences. Appendix Table B8 motivates this concern by comparing the characteristics of startups with above- and below-median experimentation objectives. Though similar on most dimensions, low-experimenting firms are larger, more likely to have a prototype, and have more funding.

Results in Columns 9-3 and 9-4 rule out this explanation by running the main specification in sub-samples split by median capital raised up to a session as an indicator of funding stage. To account for heterogeneity in capital intensiveness across technologies, I calculate median funding within technology domains. Supplemental results in Appendix Table B7 show a similar pattern using alternative measures of stage based on revenue, product development, and age since incorporation. An interesting pattern is that the angel effect is larger for more mature startups. This aligns with the skill advantage explanation. Insofar as experiments are more complex in later stages than in earlier ones, angels' skill advantage can be more relevant in more mature companies.

Sorting:

If investors' mentoring decisions are similar to the way in which they choose startups to fund, then assortative matching (Sorenson & Stuart, 2001; Hochberg *et al.*, 2007) suggests an alternative explanation. For instance, it is possible that angels are more familiar than VCs with startups in an experimentation phase due to factors that coincide with the developmental stage of the startup in which angels specialize. To examine this hypothesis, I exploit variation in the mentor-startup matches from the private meetings, before mentoring decisions are made. As noted in Section 4, these matches proxy for the fit between mentors and startups. Thus, I codify the indicator *Match* that equals 1 if a given mentor had been matched for a private meeting with a startup in the morning of the session day. The coefficient for *Match* in Column 9-5 shows that, as expected, the startup-mentor matches from the private meetings predict mentoring decisions at the end of the day, but the interaction effect shows that this effect does not differ by investor type. Column 9-6 goes one step further to show that angels' preference for mentoring experiments does not change by whether they were matched to the startup.

Information preferences:

The last possibility considered is that angels have a taste for experimentation. For instance, they may view experimenting as more informative than analysis for early-stage startups. If true, then angels should also advise startups to prioritize experiments more often than VCs do. I test this hypothesis by codifying transcribed notes from the private meetings where mentors give startups feedback on which objectives they should prioritize. These meetings take place in the morning of the session days, before the objectives are finalized in a group setting. These private feedback sessions are an excellent opportunity to capture mentors' own preferences over the importance of experimentation versus other activities.

The test here is to regress the number of experiments advised privately to the same startup on the type of the investor who gave the advice. Column 9-7 shows that angels and VCs are quite aligned in their views about the priority of experimentation. However, the insignificant effect on *Angel* can be due to high-experiment-proposing founders being ex-ante matched with angels more frequently than they are matched with VCs. Column 9-8 eliminates this concern by adding the interaction *Angel* $\times$ *Experiments*, showing that even conditional on the number of experiments proposed, angels and VCs do not disagree on the importance of experimentation. See Appendix Figure B4 for a graphical representation of these results.

8 The Advantage of VC Advice

So far, the results have focused on angels' skill advantage over VCs. This section investigates if and when VCs have an advantage over angels. The role of VCs in driving innovation and economic growth is well-documented (Samila & Sorenson, 2011). However, little is known about how VCs shape early firm development, especially in comparison to angels. A result I already show is that VCs are more likely than angels to provide advice on analysis. This is consistent with their role as professional investment managers. VCs develop specialized industry knowledge and connections (Sahlman, 1990; Gompers *et al.*, 2009), keep abreast of the latest market developments (Metrick & Yasuda, 2010), and routinely conduct financial and strategic planning (Kaplan & Sströmberg, 2004; Gorman & Sahlman, 1989). Another stream of research on VC intervention shows that they also professionalize young firms by establishing managerial structure (Hellmann & Puri, 2002; Kaplan & Stromberg, 2001). My finding that VCs drive analysis more than angels do coupled with evidence in the literature that VCs' intervene in hiring professional managers motivate asking whether VCs have a broader comparative advantage in setting up organizational structure.

Table 10 Column 10-1 shows the baseline result that VCs are more likely than angels to provide advice on analysis. Column 10-2 shows that this difference remains directionally unchanged across all tasks constituting analysis, though it is only significant for business planning. To probe the structure explanation, I start with experimentation, recognizing the fact that experiments also vary in the degree to which they contribute to organizational structure. Column 10-3 shows that the angel effect is positive and significant across all experimental tasks except for regulatory validation.[16] This is interesting and suggestive of VCs' specialization in establishing structure if we take the view that sound legal infrastructure is an organizational building concern.

To examine if VCs broadly specialize in setting structure, I create a new conceptual category for organizational development. Creating this category does not require any labeling effort–instead, I simply aggregate actions from the left column of Figure 3 that correspond to organization building. The relevant actions identified include business planning, establishing sales processes, building production capability, forming partnerships, obtaining regulatory approval, hiring, licensing and

[16] Regulatory validation pertains to the fairly homogenous operation that entails producing evidence for the viability of a regulatory pathway. This is usually done via meeting with regulatory experts (see Appendix Table D12 for details and examples of this task).

Table 10: Heterogeneity of Advice & VC Specialization in Establishing Organizational Structure

DV = Advice	(10-1)	(10-2)	(10-3)	(10-4)	(10-5)
Analysis	0.020				0.020
	(0.015)				(0.015)
Angel × Analysis	−0.078***				−0.075***
	(0.021)				(0.022)
Analytical Tasks					
Angel × Market Product Research		−0.011			
		(0.022)			
Angel × Planning (Financial, IP, Sales, Reg.)		−0.034**			
		(0.015)			
Angel × Product, Technology Roadmap		−0.055			
		(0.037)			
Experimentation Tasks					
Angel × Product Market Fit Validation			0.045**		
			(0.018)		
Angel × Technology Validation			0.079***		
			(0.020)		
Angel × Regulatory Validation			−0.041		
			(0.060)		
Organizational Development					
Org. Development				0.009	0.009
				(0.012)	(0.012)
Angel × Org. Development				−0.057***	−0.055***
				(0.018)	(0.018)
N	7,914	7,914	7,914	7,914	7,914
Mean of DV					0.120
FEs & Controls	X	X	X	X	X

Notes: This table examines the heterogeneity of angel versus VC advice across different types of activity. *Org. Development* in Columns 10-4 and 10-5 is an indicator that equals 1 when at least two of the startup's priorities are on business planning, establishing sales and production processes, forming partnerships, hiring employees, licensing, and raising capital. Put differently, this variable equals 1 if the startup's top-three priorities include two or more of the following labels described in Figure 3: $\{t_2, a_{16}, a_{19}, a_{20}, a_{21}, a_{22}, a_{28}, t_{10}, a_{33}, a_{34}\}$. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

fundraising (denoted in Figure 3 by $\{t_2, a_{19}, a_{20}, a_{21}, a_{22}, a_{28}, t_{10}, a_{33}, a_{34}\}$). The indicator *Org. Development* then equals 1 if at least two of the three prioritized objectives are in that category.

Column 10-4 shows that VCs are 46% more likely than angels to drive organizational development, consistent with the idea that professionalization is a mark of VC intervention. In Column 10-5, I add the analysis category back as a covariate, and find that estimates for both analysis and organizational development remain pretty stable compared to their baselines. This suggests that VCs drive entrepreneurial learning via analysis more than angels do, in addition to providing more advice on organizational development.

9 Discussion

Advice and entrepreneurship are inseparable. As old as commerce itself, the transmission of expertise to the less experienced has been a cornerstone of economic activity. Even the structured form of modern entrepreneurship programs can be traced at least to the documented apprenticeship practices of the merchant guilds of medieval Europe (Greif, 2006). Yet not much is known about the foundations of advice, even though such knowledge can shed light on how entrepreneurial firms evolve, fail, and succeed. In this project, I take a step forward by providing causal evidence of the effect of mentoring on the market success of startups and reporting new insights on the nature and provision of advice.

This project opens new avenues for future research. First, additional work is needed to uncover the mechanisms underlying the performance effect of mentoring on young firms. Such inquiries could yield significant insights into, among other areas, the design of mentoring programs and the vulnerabilities that challenge early-stage startups. Second, while I present extensive empirical evidence on how and why angels and VCs differ in their provision of advice, endogeneity remains a concern that should be addressed in subsequent studies.

The finding that angels and VCs differ in supporting experiments versus organizational development offers a promising case for potential complementarity that future research could explore. Such insights have implications for our understanding of how investor composition drives early firm development and growth (Hellmann *et al.*, 2021). For instance, Hsu (2004) shows that entrepreneurs accept lower valuations from more reputable investors. If investors vary significantly in the provision of support services, founders may overpay for affiliation if they overestimate the immediate legitimization benefits compared to the gradual benefits of business mentoring.

More broadly, this project unpack features of accelerators that enable answering questions in the entrepreneurship domain that have remained open due to the paucity of data. For instance, in CDL, investors choose startups, which lets the econometrician isolate investor preferences. This allows for mitigating assortative matching (Sorensen, 2007), which has plagued empirical studies in venture capital and may be responsible for some of the mixed findings. For example, while studies agree that coethnicity between VC partners and founders is highly predictive of investment decisions, Hegde & Tumlinson (2014) find a positive correlation between ethnic proximity and startup performance, while Bengtsson & Hsu (2015) find a negative correlation. Startup programs can offer research design controls that help disentangle investor-driven from founder-driven determinants of sorting dynamics.

To conclude, this project focuses on high-technology startups–a rapidly growing sector driven by technical and scientific breakthroughs in fields such as AI and space transportation. These startups hold immense potential to address humanity's most pressing challenges but are particularly difficult to build, warranting dedicated research. Given the similarities between my sample of startups and those examined in other studies, I expect my findings to be broadly applicable to the high-growth, high-technology sector. Nonetheless, a valuable next step would be to investigate whether these findings extend to other high-growth but less technology-intensive sectors.

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