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The Economics of Advice: Evidence from Start-up 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 (VCs) mentored founders over several months. Leveraging variation in mentors' availability to support start-ups because of personal scheduling conflicts, I find that advice significantly improves start-ups' future market performance. To explore how advice shapes early firm development, I develop a novel typology of start-up 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 start-ups in achieving their business objectives. Angels are more likely than VCs to help founders design and execute product market experiments, whereas 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 because of 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 start-up 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 to characterize its nature and provision by early-stage investors.

Data consist of detailed, hand-collected information on how 192 venture capitalists (VCs) and angel investors mentored 253 early-stage high-technology start-ups in building their businesses over approximately eight months. The setting is a global entrepreneurship program for technology-based start-ups called Creative Destruction Laboratory ("CDL"). Since its inception in 2012, approximately 3,500 start-ups have participated in CDL, collectively generating over $30 billion in equity value. The program involves four day-long meetings held every eight weeks at participating universities, where mentors help founders prioritize measurable business objectives and select start-ups to mentor on how to achieve those goals. For start-ups, the data set includes pre-program characteristics, longitudinal operational and financial details during the program, and post-program market outcomes. For mentors, data include their educational and professional histories, codified verbal advice given to founders, and the panel of 7,914 mentoring decisions they made to assist start-ups with achieving their prioritized business objectives. To analyze advice, I develop a novel typology of start-up activities that links 4,542 granular start-up activities to the foundations of strategy. The sample is diverse, covering start-ups in domains 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 start-up success. To establish causal evidence, I exploit variation in the personal schedules of the mentors to instrument for the amount of mentoring time that start-ups received. I find that an additional hour of mentoring increases the probability of a start-up raising more external capital than the median start-up 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 that founders would have pursued without mentor advice, I find that the characteristic element of mentor advice is to do less and learn more. Specifically, founders tend to prioritize implementing their ideas and acquiring resources, but mentors emphasize activities that generate information—in terms of both low-cost exploratory efforts and more complex market validation experiments.

Although mentors are generally consistent in their advice to prioritize analysis and experimentation, I find significant differences between angels and VCs in the business objectives that they choose to personally help start-ups achieve. Angels are more likely than VCs to mentor founders on designing and executing business experiments, whereas 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 because of their greater operational experience. This is important because as documented by Camuffo et al. (2020), I find that experimentation reduces uncertainty about start-up 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 design informative experiments and choose between strategic options. 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 (Hochberg et al. 2007, Sørensen 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 that 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 and Mukharlyamov 2022) in contrast to angels, who are predominantly ex-entrepreneurs (Linde et al. 2000, Ibrahim 2008).

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

Finally, this paper contributes to the policy debate on fostering regional start-up activity by addressing the widespread use—but limited success—of policies designed to incentivize investors (see Cumming and MacIntosh 2006 and Lerner 2009 for examples). These policies often overlook the human capital bundled with investments, failing to account for the drivers of value-added services that influence start-up growth trajectories. My findings support recent theory by Hellmann and Thiele (2019), which highlights operating experience as a driver of these services.

The findings and limitations of this study open new avenues for research. Although I discuss these opportunities in more detail later, understanding *how* mentors drive start-up 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 start-up-mentor matches, which was not feasible in my setting. Therefore, to mitigate endogeneity concerns, I employ a variety of econometric techniques, including fixed effect models, subsample analyses, tests of alternative explanations, matching approaches, and a battery of robustness checks using alternative measures and specifications.

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 start-up activities to measure advice. In Section 4, I describe how I identify the effect of mentoring on start-up 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 start-ups called 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 eight weeks, in which mentors advise founders in prioritizing three measurable business objectives to focus on for the next eight weeks and then select start-ups 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 start-ups 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 this project. Start-ups are from seven technology streams, including artificial intelligence (AI), space, and quantum computing, and one general stream for start-ups that do not fit in any of the specialized streams. There are 148 VC mentors and 44 angel mentors,[4] and there are 253 start-ups, 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 start-ups (standard deviation (SD) = 4.8) and 19 mentors (SD = 6.8), with 75% of mentors participating in a single track, 18% of mentors participating in two tracks, and the remaining 7% of mentors participating in three or more tracks. Online 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 start-up in their track. These dossiers outline the founders' proposed objectives for the upcoming eight 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 start-up's proposed objectives.

On the morning of each session day, founders meet privately with four to six 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 start-up to pursue over the next eight weeks. A business school professor moderates these debates. Sessions conclude in the early evening with deliberations, during which mentors declare start-ups that they feel equipped to mentor in achieving their finalized objectives for the following period. Figure B2 in the Online Appendix summarizes the day using a sample mentor schedule. See Online 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 start-up achieve its objectives. The modal (average) start-up receives 1 (1.61) mentor, and the modal (average) mentor selects 1 (1.64) start-up. Decisions are also high stakes for start-ups as those without formal support are dropped from subsequent sessions. CDL managers responsible for each start-up connect the founders with the mentor(s) who selected them and facilitate setting up the meetings. They also touch base with founders throughout the eight-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 and Start-ups

A mentor is an angel if from January 2018 to December 2019 (eight months before and eight months after the study cohort), the mentor made a personal investment. A mentor is a VC if the mentor made a partner investment during the same period. Investment histories are

Figure 1. (Color online) Sample Start-up 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 [redacted] (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]

Notes. This figure shows a sample start-up dossier distributed to mentors before each session. It includes updated objectives, a status update from the chief executive officer, 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 start-up are redacted.

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 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 angels 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

Figure 2. (Color online) Finalizing Objectives via a Moderated Debate

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

managerial, technical, and academic work experience. Educational background is also balanced across majors and highest degrees earned, although 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 that they commit to mentoring and the number of distinct start-ups that they choose to mentor.

Table 2 describes the 253 seed-stage companies in my sample. Pre-program information comes from start-up applications, first-session dossiers, and internet searches, whereas post-program funding data are sourced from commercial databases and validated with detailed financing terms sourced directly from founders and mentors.[5] The start-ups 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 United States-based high-technology start-up samples.

The numbers of founders (2.6) and employees (4.1) are similar to the 2.6 founders and 3.4 employees found in the sample of seed-stage start-ups in AngelList (Bernstein et al. 2017) and the 2.9 founders in the Massachusetts Institute of Technology (MIT) E-Laboratory start-ups (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 United States (Jensen and Thursby 2001). For IP appropriation strategy, Gans et al. (2002) report that funded SBIR ventures give a score of 3.5 out of 5 to the

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, years	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 Start-ups Mentored	4.50	3.09	4.07	3.36	0.45

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

Table 2. Summary Statistics of Start-ups

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
Preprogram Capital ($Million)	0.51	0	1.52	0	20
Preprogram Revenue ($Million)	0.15	0	0.49	0	5
Postprogram Funding ($Million)	3.80	0	15.90	0	218
Postprogram Valuation ($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 Start-up 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 start-ups. Financing and revenue amounts are in Canadian dollars. IPS, intellectual property strategy.

importance of patenting. Following their methodology, I label a binary variable equal to one if founders state that they protect their intellectual property by patenting. Seventy-one percent state that they are or will be using patenting as their IP protection strategy, although likely a much lower fraction will file for or be granted a patent; during the eight-month study period, only 13% did.

The median amounts of capital raised and revenues generated before joining the program are zero, reflecting the early stage of the start-ups in my sample. The mean capital raised before joining the program is approximately U.S. $370,000, which is higher than the U.S. $304,000 for AngelList start-ups (Bernstein et al. 2017). Assuming that start-ups 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 start-ups that received their first round of VC funding between 2002 and 2010 (Ewens et al. 2018).

Moving to founder characteristics in panel B of Table 2, 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 start-ups in the MIT E-Laboratory and MIT Venture Mentoring Services (Scott et al. 2020). The average team age of 34 years old is younger than the age of 40 years old found in Ewens et al. (2018) and the 2010 Global Entrepreneurship Monitor (Liang et al. 2018), although neither of these samples are 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 and Mason 2007).

3. A Novel Typology of Early-Stage Start-up Activities

Figure 3 displays the classification system that I developed and use to categorize start-up objectives. This classification leverages 4,542 business objectives extracted from venture dossiers (see the top of Figure 1) to link granular start-up activities to the foundations of strategy. Akin to the case study method of Eisenhardt (1989), I developed this model by documenting early firm development in several hundred start-ups 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 start-up activities; then, I use a replicable labeling procedure to classify business objectives from my setting into these categories. The present work builds on and extends a few but notable existing classifications by Carter et al. (1996), Reynolds (2001), and Bennett and Chatterji (2023). In Online Appendix Table D1, I note similarities and differences between my classification and each of these existing efforts.

3.1. Conceptual Categories

Starting with experimentation, I follow an established literature to define it as tests that create real options concerning product, market, and regulation (Kerr et al. 2014, Manso 2016, Levinthal 2017).[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

Figure 3. Typology of Start-up Activities

Notes. This figure shows a hierarchical typology of start-up 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 center column called Tasks is a list of 12 coarse business tasks that contain related business functions. The right column called Conceptual Categories corresponds to the four types of start-up activities derived from the literature. The connecting lines show the mapping from activities to conceptual categories used to label individual business objectives. ML, machine learning; MVP, minimum viable product; POC, proof of concept.

(McGrath and 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 (Delmar and Shane 2003, Shane and Delmar 2004).[7]

Compared with 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, whereas 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 start-ups.

Table 3. Four Conceptual Categories of Start-up Activities

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

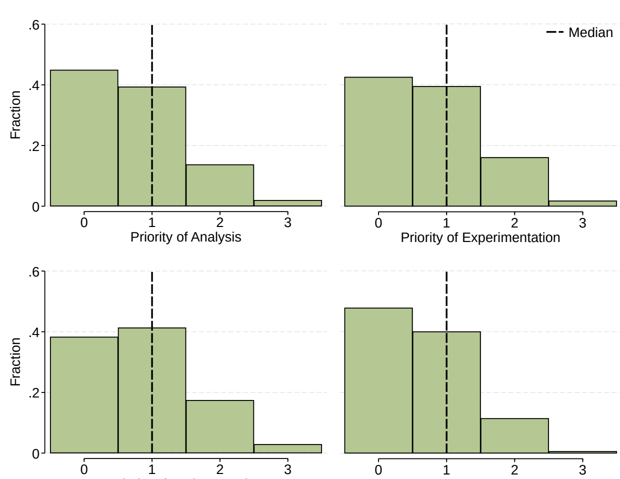
Notes. This table shows the key features of and stylized examples for each of the conceptual categories.

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 start-up objectives. Interestingly, the median occurrence of categories in firms' prioritized objectives is roughly equal, indicating the balanced importance of the conceptual categories.

3.2. 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 and 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 center column in Figure 3 shows a set of coarser business tasks that summarize bundles of similar business functions.

Figure 4. (Color online) Distribution of Conceptual Categories in Prioritized Objectives



Note. This figure shows the distribution of conceptual categories in start-ups' top-three prioritized objectives.

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 that 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 gave three undergraduate students the 34 activity labels and the raw text of the objectives, then asked them to assign one label to each objective based on their understanding of the labels and the raw text of the objective. The intersection of their labels matches mine in 95% of the cases. In Online Appendix Table D2, I catalog examples and exclusions for each of the activity classes. To illustrate the iterative labeling procedure, Table D2 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 and Market Performance

This section outlines the empirical strategy used to estimate the effect of mentoring on start-up market performance. Estimation approaches for the other analyses are detailed separately within their respective results sections.

4.1. 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 start-up's amounts are higher than the median funding and valuation among start-ups 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*, which is equal to one if the firm is still active. This variable accounts 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.

4.2. Estimation

Regressions are specified as

$$y_i = \alpha + \beta_1 Mentoring_i + \boldsymbol{x}_i \boldsymbol{\beta}_2 + \gamma_i + \delta_i + \epsilon_i. \quad (1)$$

$Mentoring_i$ is the total hours of mentoring excluding those committed at session 1 to allow for comparison between OLS and instrumental variable (IV) results. As we will see, I do not have an instrument for the mentoring commitments that start-ups receive at the first session, although 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 start-up-specific indicators γ_i and δ_i correspond to the site and technology stream in which start-ups participate.

4.3. 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 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 start-up because of 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.

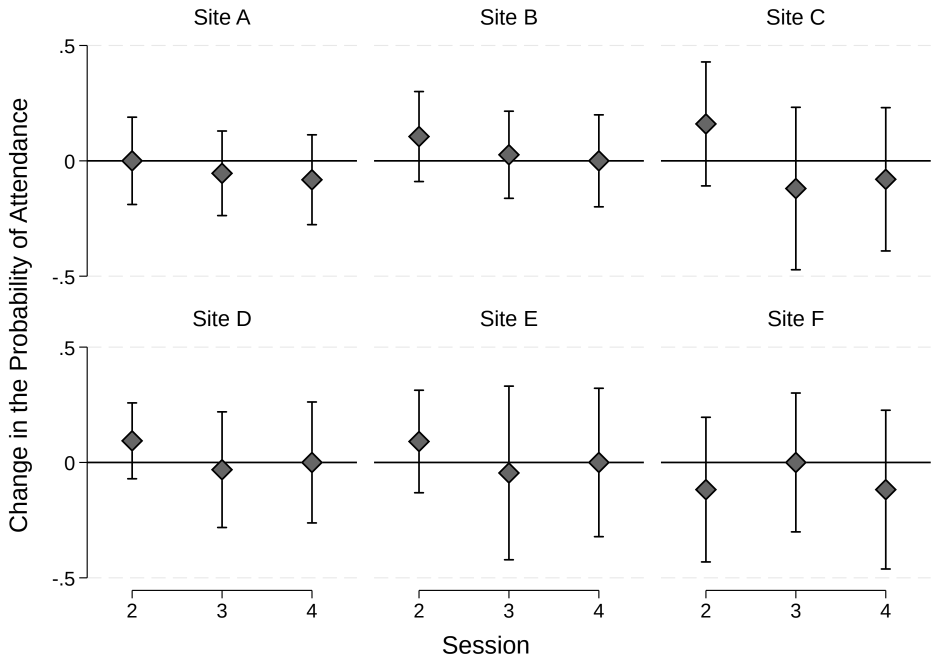
The first step in building this IV is to identify the set of good-fit mentor-start-up matches that are determined by neither founders nor mentors. The set of start-up-mentor matches for private meetings that take place in the morning of session days is an excellent proxy. In preparation for the first session, CDL managers determine the founder-mentor match-ups based on their knowledge of each start-up's business and each mentor's expertise and preferences. The more of these mentor matches for a given start-up that happen to attend the second session, the higher the chances of that venture receiving mentoring time commitments. At the second session, some matches are new, again marking the first time that 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 start-up 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.

4.4. Exclusion Restriction

The validity of the exclusion restriction rests upon the assumption that mentors' personal schedules are not related to the quality of start-ups, except through the mentoring support. 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, which depicts within-mentor estimates of the probability of attending sessions by site. There are no discernible patterns.

However, the fact that start-ups that receive no mentor commitments are dropped from subsequent sessions poses a threat to the validity of the exclusion restriction. Consider a start-up that is dropped at the third session, despite having a matched mentor present, perhaps because of 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,

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 denotes indicators for sessions with session 1 as the omitted and β_j denotes 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% confidence intervals falling outside of zero.

thus allowing venture survival in the program to open a path between firm quality and the instrument, violating the exclusion restriction.

Because the issue is the possibility that unobserved quality encoded in CDL survival outcomes affects the value of the IV, this path can be blocked by running regressions in samples conditioned on start-ups *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 start-up attending that session. In this construct, whether 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 in Table 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 in Table 4 shows that an additional hour of mentoring is associated with a 0.58% increase in the probability of survival. Table B1 in the Online Appendix 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.

5.1. IV Estimates

Table 5 presents the two-stage least squares (2SLS) estimates of the relationship between mentoring and market performance. Column 5-1 in Table 5 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 in the probability that an additional mentor commits to provide mentoring advice over the next eight-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 in Table 5 have the same sign as and are similar in magnitude to the corresponding OLS results. The slight increase in magnitude could be because of the local nature of the effects. The IV estimates reflect the causal effect of mentoring on success for start-ups affected by mentors' idiosyncratic schedule conflicts, presumably start-ups that may experience a higher marginal benefit from mentoring.

As noted earlier, the CDL program's design to drop start-ups that receive no mentoring at a given session

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

Dep. Var.	*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)
Preprogram Capital ($Million)		0.012		0.012		0.005
		(0.021)		(0.021)		(0.007)
Preprogram Revenue ($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 FEs		X		X		X
Stream FEs		X		X		X

Notes. This table shows the OLS estimates of the relationship between mentoring and start-up performance. Dependent variables are indicated in column headers. *Mentoring Hours* indicates the total hours that mentors committed to the start-ups from the second session onward. Robust standard errors are in parentheses. Statistical significance is denoted by asterisks. IPS, intellectual property strategy.

*10%; **5%; ***1%.

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 because the disaggregated value of the IV for a given session is not affected by whether the start-up gets dropped at that session. Table B2 in the Online Appendix displays these estimates with above-median funding as the dependent variable. Results with above-median valuation as the dependent variable are similar. Overall, estimates are consistent with the full-sample results with two notes. First, although 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 one session.

These findings establish a large and significant causal link between mentoring and the market performance of start-ups, 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 upper panel of Figure 6 shows the fraction of objectives in each

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

	First stage	Second stage		
Dep. Var.	5-1 *Mentoring Hours*	5-2 *AbvMed Funding*	5-3 *AbvMed Valuation*	5-4 *Alive*
Mentoring Hours		0.016*** (0.003)	0.016*** (0.003)	0.008*** (0.003)
Matched Mentors Attending	0.848*** (0.040)			
F statistic	450			
Controls	X	X	X	X
N	253	253	253	253

Notes. This table shows the 2SLS estimates of the relationship between mentoring and start-up performance. Dependent variables are indicated in column headers. *Mentoring Hours* indicates the total hours that mentors committed to the start-ups from the second session onward. Controls are the same as in column 4-2 of Table 4. Robust standard errors are in parentheses. Statistical significance is denoted by asterisks.
*10%; **5%; ***1%.

conceptual category by whether objectives are from the set that founders proposed before the mentoring sessions or from the set finalized at the end of the session day. Relative to mentors, founders significantly underprioritize 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 lower 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.

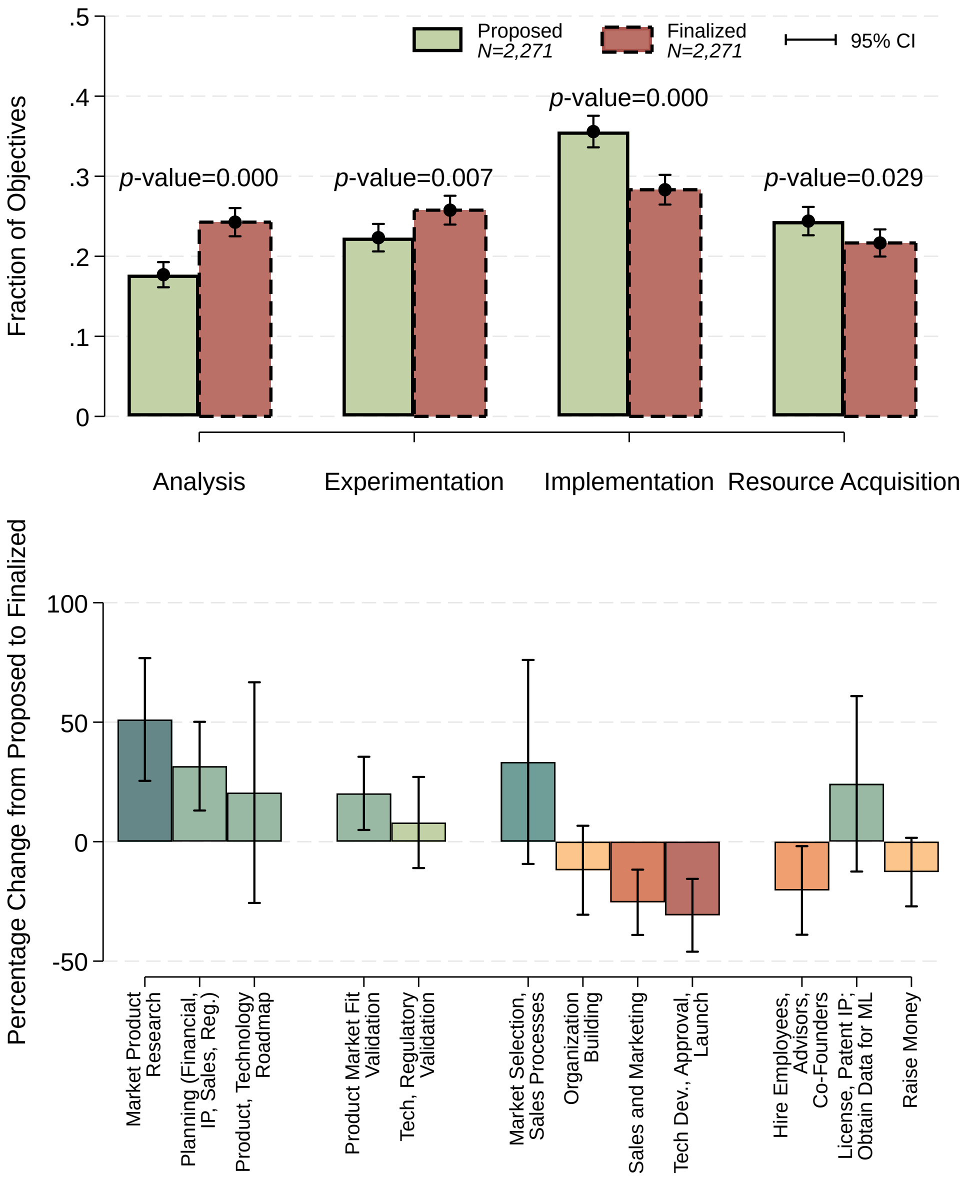
An interpretation of these results is that mentors nudge entrepreneurs away from activities that entail significant commitments. Even among learning activities, the largest increases occur in low-commitment and noisy approaches, such as search and planning. Conversely, the largest decreases are in tasks requiring significant commitments to specific product market ideas. A more magnified view in Table D3 in the Online Appendix shows that the only product-market implementation activity *not* reduced is *Obtain Regulatory Approval*, which itself can be thought as a product validation exercise. There is also a large, although insignificant, increase in *Market Selection, Sales 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 toward 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 toward implementation and resource acquisition.

6.1. The Provision of Advice: Angels vs. 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 nonfinancial 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 and Lerner 2000, Samila and Sorenson 2011) but also vary significantly in their ability to grow start-ups (Sørensen 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

Figure 6. (Color online) Differences Between Proposed and Finalized Objectives



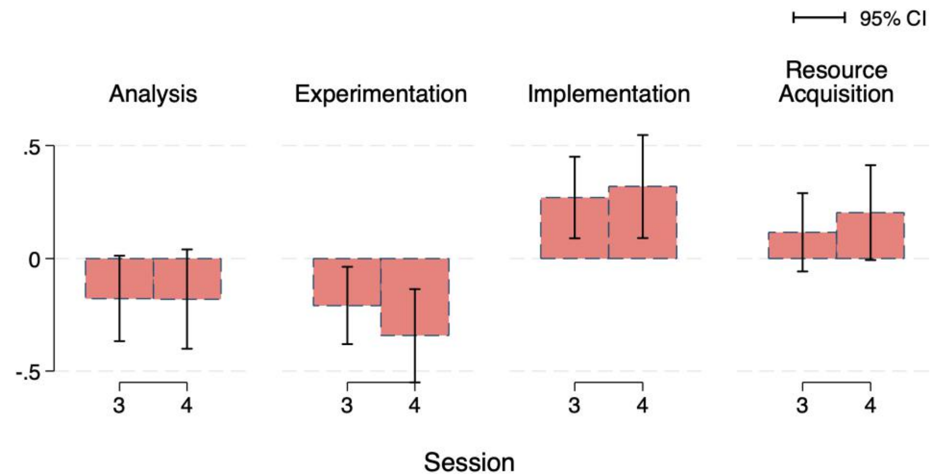
Notes. The upper panel shows the average fraction of objectives in each conceptual category in proposed and finalized objectives. The *p*-values correspond to *t* tests of differences in shares between proposed and finalized objectives. The lower panel shows the percentage change in the fraction of tasks from proposed to finalized. The error bars display 95% confidence intervals of the *t* test that differences are significantly different from zero. ML, machine learning.

(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 start-ups 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 (one or zero 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, Table B3 in the Online Appendix shows that the share of experimentation objectives in top-three priorities is 26% higher among angel-mentored start-ups than among VC-mentored ones. Figure 8 also shows that VCs are instead more likely than angels to provide advice on analysis, whereas the remaining panels of Figure 8 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

Figure 7. (Color online) 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 the 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 2. Session 1 observations are dropped because of missing lagged objectives. Regressions include venture fixed effects, and standard errors are clustered by start-up.

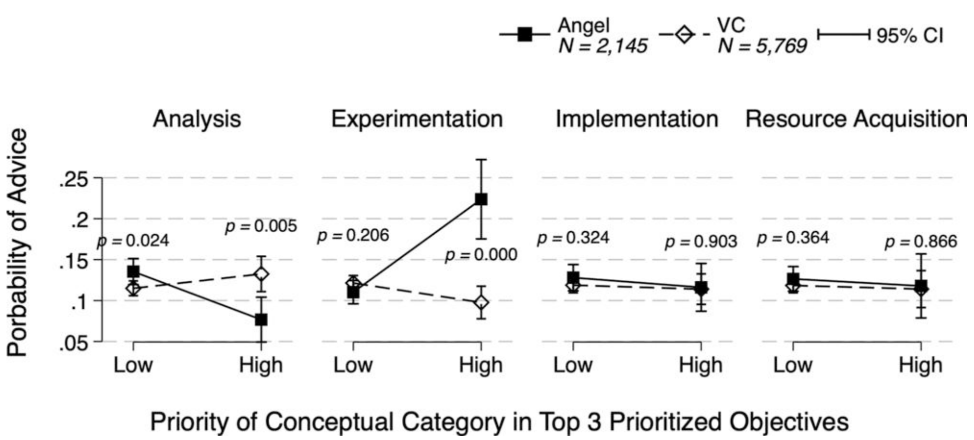
entrepreneurial process, but increasingly, scholars have also warned against the unintended consequences of reckless experimenting. As the first step in unpacking the experimentation results, I tackle the main endogeneity concerns with more sophisticated multivariate methods. Chief among these concerns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

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

$$Advice_{ijt} = \beta_1 Angel_i \times Experiment_{jt} + \beta_2 Experiment_{jt} + \boldsymbol{x}_{jt}\boldsymbol{\beta}_3 + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt}, \qquad (2)$$

where $Advice_{ijt}$ is an indicator that equals one if mentor i chooses to advise start-up j on achieving its session t objectives, $Angel_i$ is an indicator that equals one if mentor i is an angel and zero if mentor i is a VC, and

Figure 8. The Probability of Angel vs. 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 start-ups on achieving the business objectives prioritized for the next eight weeks. In the Analysis panel, low means that one or none of the top three objectives are analyses, and high means that two or three of the start-up's top three objectives for the next eight 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 start-ups on how to achieve their prioritized objectives.

$Experiment_{jt}$ is an indicator that equals one if the majority—two or three—of start-up j's three prioritized objectives at session t are to experiment. The mentor and start-up fixed effects, denoted by γ_i and δ_j, account for the unobserved qualities of start-ups and mentors. Session fixed effects denoted by η_t allow for comparing objectives initiated during the same period.

Fixed effects remove some of the major concerns, but changes in the growth potential of start-ups 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 start-up's growth trajectory. These controls are $RevenuePositive_{jt}$, which equals one if the start-up is revenue positive to account for investor risk preferences; $AbvMedFunding_{jt}$, which equals one if total funding is above median to account for round size preferences; and $OpenRound_{jt}$, which equals one if the start-up 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.

6.1.2. Estimates. Table 6 shows OLS estimates of Equation (2). Columns 6-1 and 6-2 in Table 6 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 two times—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 that 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. Results in Table B5 in the Online Appendix 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 that VCs are comparatively more likely to

Table 6. Provision of Experimentation Advice by Angels and VCs

Dep. Var. = *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
Start-up FEs		X	X	X	X	X
Mentor FEs				X	X	X
Session FEs					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 denoted by asterisks.
*10%; **5%; ***1%.

support. Online Appendix 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 than VCs to mentor start-ups in designing and running 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 because of 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.

6.2.1. 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 that 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 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 in Table 7 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.

6.2.2. 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 start-up. I leverage these variations to estimate regressions of the form

$$\begin{aligned} Advice_{ijt} = {} & \beta_1(Experiment_{jt} \times MentorExpr_i \times TeamExpr_j) \\ & + \beta_2(Experiment_{jt} \times MentorExpr_i) \\ & + \beta_3(Experiment_{jt} \times TeamExpr_j) \\ & + \beta_4(MentorExpr_i \times TeamExpr_j) \\ & + \beta_5 Experiment_{jt} + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt}, \end{aligned} \tag{3}$$

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

Figure 9 visualizes the results. The left panels of Figure 9 measure mentor experience using exit; the right panels of Figure 9 measure it as prior founding history. The upper panels of Figure 9 measure team experience as prior founding history; the lower panels of Figure 9 measure it as start-up work experience. The top estimates in each panel of Figure 9 show whether experienced mentors provide more experimentation advice than inexperienced mentors to teams without any start-up experience (β_2), and the bottom estimates in each panel of Figure 9 show this for teams with start-up experience (β_1).

Across the board, experienced mentors provide more experimentation advice but only to inexperienced teams. Figure B3 in the Online Appendix shows that this result does not hold for other activity types, meaning that the experimentation effect is not driven by general

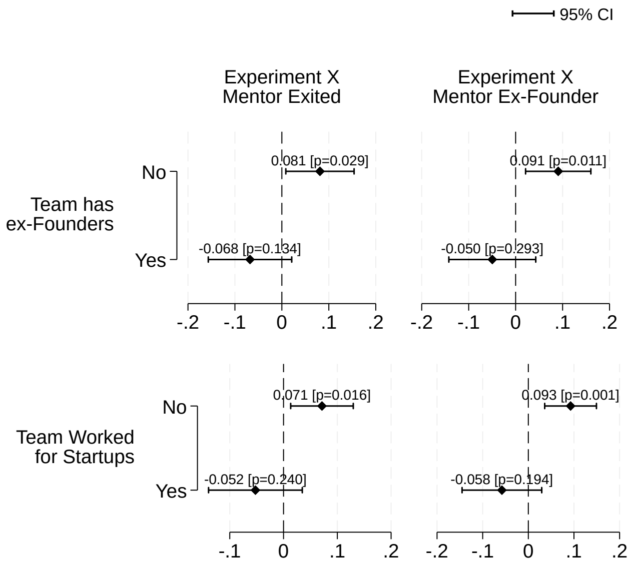
Table 7. Operating Experience and Provision of Experimentation Advice

	Sample of angel decisions		Sample of VC decisions	
Dep. Var. = *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
Controls	X	X	X	X

Notes. This table shows the likelihood of providing experimentation advice in subsamples of angels and VCs split by exit history. Controls are identical to those in the fully specified column 6-6 of Table 6. Standard errors clustered by mentor are reported in parentheses. Statistical significance is denoted by asterisks.

*10%; **5%; ***1%.

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



Notes. This figure plots estimates from Equation (3). 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 β_1: the marginal difference in providing experimentation advice by experienced mentors to experienced founding teams. The *p*-values for the significance of each estimate are reported in square brackets.

substitutions in the human capital stocks of mentors and mentees.

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 start-up achieved each of its objectives.[13] Completion is an appropriate measure of advice quality for two reasons. As Hellmann and 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 that founders seek in *smart money* to unlock additional resources. If the session-day feedback given by experts approximates the true start-up priorities better than those initially proposed by mostly inexperienced founders, then variation in the completion of prioritized tasks contains information about the quality 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-start-up 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-start-up fixed effects in addition to the existing mentor and session fixed effects. Specifically, I estimate

$$Completion_{ijst} = \beta_1 Angel_i \times Experiment_{jst} + \beta_2 Experience_i \times Experiment_{jst} + \gamma_i + \delta_{js} + \eta_t + \epsilon_{ijst}, \tag{4}$$

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

The first three columns of Table 8 report the estimates, indicating that only prior operating experience is significantly associated with the likelihood of completing experiments. Also, as expected, angel-mentored start-ups are more likely to complete their experiments than VC-mentored start-ups, although 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 if 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 a series of tests in Online Appendix C. For the first problem, I employ inverse probability of treatment weighting to attenuate bias. For the second problem, I re-estimate Equation (4) 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.

6.3.1. 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' more accurate beliefs about start-up quality. To measure belief precision, I code an indicator that equals one if the start-up 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 start-up never gets dropped.[15] Put differently, mentor beliefs would be less precise if after eight weeks of mentoring the start-up and observing the

Table 8. Quality of Experimentation Advice

Dep. Var.	*Completion*			*Immediate Drop or Graduation*	
	(8-1)	(8-2)	(8-3)	(8-4)	(8-5)
Sample:	Full	Full	Full	Session 1	Session 1 and 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	2,393	209	120
Mean of DV			0.565	0.670	0.683
Mentor FEs	X	X	X		
Session FEs	X	X	X		
Start-up × task FEs	X	X	X		
Stream FEs				X	X
Site FEs				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 are at the start-up-session-objective-mentor level, 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. Forty-four start-ups that attended their first in-person meeting at session 2 or later are dropped. Standard errors clustered by site are in parentheses. Statistical significance is denoted by asterisks.
*10%; **5%; ***1%.

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 start-up from the program. The statistical approach then regresses this outcome on the types of activity attempted and completed since the first session.

The remaining two columns in 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 start-ups 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 start-up, such as help with fundraising, are satisfied. In column 8-5 in Table 8, I condition the sample on start-ups 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. 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 and Spina 2024).

7. Alternative Explanations

Because random assignment of mentors and advice is infeasible, I employ various econometric techniques to mitigate major endogeneity concerns. However, these approaches do not entirely rule out important alternative explanations. In this section, I identify and examine four primary alternatives: (1) deal flow incentives, (2) stage preferences, (3) sorting, and (4) information preferences. Table 9 summarizes the key tests for each alternative, while supplemental analyses using additional

Table 9. Tests of Alternative Explanations

Explanation: Dep. Var.	*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*** (0.032)	0.115*** (0.040)	0.129*** (0.036)	0.171*** (0.049)	0.116*** (0.028)	0.102*** (0.032)		
Matched					0.351*** (0.028)	0.356*** (0.029)		
Angel × Matched					0.065 (0.056)	0.043 (0.059)		
Matched × Experimentation						−0.026 (0.068)		
Angel × Matched × Experimentation						0.109 (0.105)		
Angel							−0.021 (0.064)	−0.066 (0.068)
Proposed Experiments							0.566*** (0.062)	0.538*** (0.058)
Angel × Proposed Experiments								0.077 (0.096)
N	3,899	4,015	4,413	3,501	7,914	7,914	411	411
Start-up FEs	X	X	X	X	X	X	X	X
Mentor FEs	X	X	X	X	X	X		
Session FEs	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 denoted by asterisks.
*10%; **5%; ***1%.

measures are presented in Table B7 in the Online Appendix.

7.1. Deal Flow Incentives

The most salient alternative explanation is because of 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 that start-ups 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, start-ups 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 start-ups. Columns 9-1 and 9-2 in Table 9 run the main specification in subsamples of start-ups 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 because investors can anticipate the need to raise in the future. In the supplemental tests shown in Table B7 in the Online Appendix, 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 runs out of cash.

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 higher-quality start-ups 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 start-up quality to exclude others from investing because start-ups 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 Online Appendix A, I provide a more extensive discussion on this matter.

7.2. 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. Table B8 in the Online Appendix motivates this concern by comparing the characteristics of start-ups with above- and below-median experimentation objectives. Although 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 in Table 9 rule out this explanation by running the main specification in subsamples 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 Table B7 in the Online Appendix 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 start-ups. 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.

7.3. Sorting

If investors' mentoring decisions are similar to the way in which they choose start-ups to fund, then assortative matching (Sorenson and Stuart 2001, Hochberg et al. 2007) suggests an alternative explanation. For instance, it is possible that angels are more familiar than VCs with start-ups in an experimentation phase because of factors that coincide with the developmental stage of the start-up in which angels specialize. To examine this hypothesis, I exploit variation in the mentor-start-up matches from the private meetings before mentoring decisions are made. As noted in Section 4, these matches proxy for the fit between mentors and start-ups. Thus, I codify the indicator *Match* that equals one if a given mentor had been matched for a private meeting with a start-up in the morning of the session day. The coefficient for *Match* in column 9-5 shows that, as expected, the start-up-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 start-up.

7.4. 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 start-ups. If true, then angels should also advise start-ups to prioritize experiments more often than VCs do. I test this hypothesis by codifying transcribed notes from the private meetings where mentors give start-ups 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 start-up 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 because of 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* × *Experiments*, showing that even conditional on the ex ante number of experiments proposed, angels and VCs do not disagree on the importance of experimentation. See Figure B4 in the Online Appendix 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 and Sorenson 2011). However, little is known about how VCs shape early firm development, especially in comparison with angels. A result that 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 and Yasuda 2010), and routinely conduct financial and strategic planning (Gorman and Sahlman 1989, Kaplan and Strömberg 2004). Another stream of research on VC intervention shows that they also professionalize young firms by establishing managerial structure (Kaplan and Stromberg 2001, Hellmann and Puri 2002). My finding that VCs drive analysis more than angels, 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.

Column 10-1 in Table 10 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, although 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 in 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 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 one if at least two of the three prioritized objectives are in that category.

Column 10-4 shows that VCs are 47% 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 stable compared with their baselines. This suggests that VCs drive entrepreneurial learning via analysis more than angels do in addition to providing more advice on organizational development.

Table 10. Heterogeneity of Advice and VC Specialization in Establishing Organizational Structure

Dep. Var. = *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 Road Map		−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
Controls	X	X	X	X	X

Notes. This table examines the heterogeneity of angel vs. VC advice across different types of activity. *Org. Development* in columns 10-4 and 10-5 is an indicator that equals one when at least two of the start-up's priorities are on business planning, establishing sales and production processes, forming partnerships, hiring employees, licensing, and raising capital. Put differently, this variable equals one if the start-up's top-three priorities include two or more of the following labels described in Figure 3: $\{t_2, a_{19}, a_{20}, a_{21}, a_{22}, a_{28}, t_{10}, a_{33}, a_{34}\}$. Controls are identical to those in the column 6-6 of Table 6. Standard errors clustered by mentor are reported in parentheses. Statistical significance is denoted by asterisks.

*10%; **5%; ***1%.

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 start-ups 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 start-ups. Second, although 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 with the gradual benefits of business mentoring.

More broadly, this project unpacks features of accelerators that enable answering questions in the entrepreneurship domain that have remained open because of the paucity of data. For instance, in CDL, investors choose start-ups, which lets the econometrician isolate investor preferences. This allows for mitigating assortative matching (Sørensen 2007), which has plagued empirical studies in venture capital and may be responsible for some of the mixed findings. For example, although studies agree that coethnicity between VC partners and founders is highly predictive of investment decisions, Hegde and Tumlinson (2014) find a positive correlation between ethnic proximity and start-up performance, whereas Bengtsson and Hsu (2015) find a negative correlation. Start-up 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 start-ups—a rapidly growing sector driven by technical and scientific breakthroughs in fields such as AI and space transportation. These start-ups have immense potential to address some of humanity's most pressing challenges, yet they are especially challenging to build and therefore merit dedicated research. Given the similarities between my sample of start-ups 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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Endnotes

[1] A 2009 OECD report estimates the sizes of angel and VC markets in the United States at $18.3 and $17.7 billion, respectively, and in Europe at $5.3 and $5.6 billion, respectively. These statistics are consistent with a later OECD (2011) report and estimates by Mason and Harrison (2002) and Sohl (2003). Although 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 Figure B1 in the Online Appendix for a snapshot of the fund's home page). The recent proliferation of micro-VCs indicates continued growth in the seed-funding market (Amore et al. 2023).

[2] Some theorists assume that angels are arm's-length investors who provide limited or no value (Bergemann and Hege 2005, Chemmanur and Chen 2014), whereas others assume the opposite (Leshchinskit 2002, Casamatta 2003). The muddle also exists in practice. Regulatory guides, such as that of 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).

[3] The matching of start-ups 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 start-ups, and start-ups rank tracks.

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

[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 that 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.

[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."

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

[9] This should not happen because by design, CDL instructs mentors to base their mentoring decisions on their ability to help the start-up achieve its objectives, not perceived quality. The purpose of the cutting mechanism is to progressively focus mentoring resources on start-ups that at least one participating mentor finds capable of supporting. Furthermore, clearly low-quality start-ups (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.

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

[11] Although the response variable is binary, I use LPM because nonlinear models, such as logistic, produce inconsistent estimates with multiway fixed effects because of the incidental parameter problem (Kwak et al. 2023). The issue is less severe when there are many observations for each effect (e.g., several start-up-mentor observations for each session fixed effect) and more severe when there are few observations for each effect (e.g., a handful of mentor-session observations for each venture fixed effect). 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.

[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 start-up, and the latter has less experience than a founder who grows the firm to a mature stage. To the extent that 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.

[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.

[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. Because of the highly risky nature of start-up 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.

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

[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 Table D2 in the Online Appendix for details and examples of this task).

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