Are Angel Investors More Likely than Venture Capitalists to Drive Entrepreneurial Experimentation?

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Abstract

Although angel investors and venture capitalists (VCs) both participate in the supply side of the same market, providing capital and advice to startup firms, they are distinct in several ways. The differences in when they deploy capital are well studied. The differences in when they provide advice are not. Using a sample of 7,914 mentoring decisions by seed-stage investors from which I construct a novel typology of startup activities, I report among the first empirical findings on systematic differences in angel advice versus VC advice. Angels are more likely than VCs to provide advice on the design and execution of experiments, whereas VCs are more likely than angels to provide advice on analysis. While analysis is a skill that can be learned from studying, hypothesis testing is a skill developed via learning-by-doing. I report evidence consistent with the hypothesis that angels are more likely to provide experimentation advice because they have a skill advantage in that domain due to operational experience.

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1 Introduction

A familiar dilemma for early-stage entrepreneurs is whether to raise capital from angel investors ("Angels") or venture capitalists ("VCs"). Angels and VCs compete to fund scalable ideas by deploying a roughly equal amount of early-stage capital,[1] but they differentiate themselves by the promise of their value-added services (Hsu, 2004). Particularly in early-stage ventures, the extensive mentoring role of investors can be instrumental in setting a path to success (Kaplan & Sströmberg, 2004; Kerr *et al.*, 2014a; Bernstein *et al.*, 2016). However, we know surprisingly little about how the two competing sources of risk capital differ in mentoring startups. In this paper, I use rich hand-collected panel data to report the first series of evidence on systematic differences between angels and VCs in the provision of advice. Specifically, I ask: are there systematic differences in the type of advice that angels provide compared to VCs? If so, then why do they differ?

The theoretical literature has made conflicting assumptions about the value-added potential of angels versus VCs. Some theorists assume angels are arm's-length investors who provide limited or no value (Bergemann & Hege, 2005; Chemmanur & Chen, 2014), while others assume the opposite (Leshchinskit, 2002; Schwienbacher, 2009; Casamatta, 2003). The muddle is just as clear in practice. Regulatory guides such as the SEC (2022) underscore a more active mentoring role for VCs than angels, whereas the popular press often views substantial mentoring as a key feature of angels (e.g. New York Times, 2015). A striking implication is for technology-based startups that depend on advice from their investors to make early business decisions. Often run by technical founders, these high-potential ideas are especially prone to making early strategic mistakes that are costly to reverse (Eisenhardt & Schoonhoven, 1990).

On the surface, it may appear that entrepreneurs do not need mentors as long as they experiment. As central as experimentation is to the entrepreneurial process (Kerr *et al.*, 2014b; Nanda & Rhodes-Kropf, 2017; Manso, 2016), however, it is also costly. Experiments entail non-trivial costs, such

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

as partial commitments that foreclose the option to abandon bad ideas (Gans *et al.*, 2019), or conversely, the potential to dilute high-impact ideas into incremental innovations (Felin *et al.*, 2020). In other words, successful commercialization requires also "a lot of learning how to learn" (Nelson, 1997). The first significant evidence that entrepreneurs can learn how to experiment is RCT results by Camuffo *et al.* (2020) who show that introducing founders to the scientific approach of hypothesis testing increases the informativeness of business tests they run.

Agrawal *et al.* (2021) argue that the costly nature of experimentation creates a role for mentors who can help entrepreneurs design and run informative experiments. This is consistent with the broader finding that effective mentoring focuses advice on when and how to invest effort in learning (Cohen *et al.*, 2019b; Chatterji *et al.*, 2019). Combined with the fact that angels and VCs compete by providing a bundle that includes *both* capital and advice, and given that capital is essentially a commodity, there are important practical and theoretical implications of understanding how these two major sources of advice differ in providing advice. Put simply, advice may be the biggest differentiator between the two choices.

To explore these questions, I hand-collect a panel of 7,914 mentoring decisions made by 192 VCs and angels to help early-stage, high-technology startups achieve measurable business objectives. The setting is a global science-based entrepreneurship program ("SEP") with over $28 billion of equity value created from the first ten cohorts of its participating firms. This is an excellent setting for my study because the key variables of interest are unusually detailed in a manner that enables measurement. Specifically, the program is structured as a series of in-person meetings held every eight weeks where mentors make costly decisions as to which startups they wish to support in achieving specific objectives prioritized for the next eight-week period.

The empirical analysis compares changes in the type of startup objectives over time–the prioritized tasks investors can choose to help startups accomplish–to explain variation in the mentoring decisions of angels versus VCs. To tackle endogeneity concerns, I start by using fixed effects that focus the comparison within mentors, startups, and time periods, while controlling for time-varying features of startups. Further, I examine several alternative explanations based on mentor financial incentives, sorting, information preferences, and startup stage preferences. In addition, I employ matching techniques to assess the effectiveness of advice and underlying mechanisms. Lastly, I test the robustness of my findings against a battery of alternative specifications.

Baseline results show that although angels and VCs are approximately equally likely to provide advice, they indeed differ systematically in the type of advice they provide. Specifically, Angels are significantly more likely than VCs to provide advice on the design and execution of experiments (e.g., to establish product-market fit), but this is not the case for other types of activity such as the implementation of ideas (e.g., manufacturing and marketing operations) or acquisition of resources (e.g., financing). On the other hand, VCs are more likely than angels to provide advice on *analysis* (e.g., financial planning, market research). Analysis is just as pervasive as experimentation among startups' top objectives, suggesting potential complementarities between advice by angels and VCs.

In terms of mechanisms, I report evidence consistent with the hypothesis that angels have a skill advantage in experimentation due to having more operational experience. This result extends the finding that entrepreneurial experience endows superior learning practices (Gompers *et al.*, 2010; Goldfarb & Xiao, 2011; Gruber *et al.*, 2008) by providing evidence that experimentation is a skill developed via learning-by-doing (Gans, 2018). It also helps resolve the puzzling observation that angels are competitive with VCs in early-stage funding, despite lacking VCs' institutional scale. If experiments are critical to early firm development, angels may compete with VCs by providing more hands-on support, powered by their distinct type of human capital. This explanation squares with the fact that only 7% of all VCs possess substantive entrepreneurial experience (Gompers & Mukharlyamov, 2022), in contrast to angels who are predominantly ex-entrepreneurs (Ibrahim, 2008; Linde *et al.*, 2000).

The foremost contribution of this paper is to overcome the persistent challenge of measuring and analyzing advice. In doing so, I shed light on the prominent mentoring role of investors (Kaplan & Sströmberg, 2004; Sahlman, 1990; Gorman & Sahlman, 1989), and add to our understanding of the link between investor human capital and early firm development (Sorensen, 2007; Hochberg *et al.*, 2007; Barrot, 2017; Gompers & Mukharlyamov, 2022). By comparing angels with VCs, I also respond to longstanding calls for research on how these two competing sources of capital differ in supporting nascent startups (Da Rin *et al.*, 2013; Chemmanur & Chen, 2014; Hellmann & Thiele, 2015). This paper also contributes to the growing literature on design characteristics of startup accelerators and their impact on regional economies (Hallen *et al.*, 2020; Hochberg, 2016; Cohen *et al.*, 2019a).

My high-technology setting contributes to an emerging literature that recognizes the unique challenges of this sector (Hsu, 2007b). Startups that commercialize advanced technologies hold the potential to solve humanity's most pressing problems, yet they face high levels of technical and commercialization challenges (Arora *et al.*, 2024). One source of these challenges is difficulties in attracting human resources (Bryan *et al.*, 2022; Roach & Sauermann, 2023). Another source is difficulties in attracting financial resources. On the latter, Nanda *et al.* (2023) note potential disagreements between founders and investors on which experiments to prioritize, limiting the range of investors willing to fund them. Lerner & Nanda (2020) point out a recent response by VCs to move upstream towards incubating and mentoring ideas in-house before financing. This model is reminiscent of my setting where investors mentor startups *before* investing.[2]

In terms of policy implications, this paper speaks to the popular use but the rare success of policies that aim to boost regional startup activity by offering financial incentives to investors (see Lerner (2009) and Cumming & MacIntosh (2006) for two examples). These policies are often invariant to the human capital that is bundled with the capital investors provide, thus ignoring the antecedents of value-added services that shape young firms' growth trajectories. My results support recent theory by Hellmann & Thiele (2019) that the prior operating experience of investors is an important input to creating robust entrepreneurial ecosystems.

The rest of this paper is organized as follows. The next section describes the empirical setting and sample characteristics, followed by Section 3 on the main approach to statistical analysis. Section 4 presents the novel typology of startup activities that I develop to measure advice. I then transition to showing the results, with Section 5 on the main findings, Section 6 on testing alternative explanations, and Section 7 on mechanisms. The final set of findings shown in Section 8 is an exploration into the comparative role of VCs in driving organizational development. I close the paper in Section 9 with discussing implications for present and future research.

2 Empirical Setting

Analyzing investor advice faces two basic data availability problems. In early-stage venture capital, quantitative financial indicators such as valuation are often difficult to access, much less qualitative

[2] Indeed, SEP was founded on the thesis that investors' business judgment is a more critical input to technology commercialization than just the capital they inject.

measures pertaining to non-financial services. Even with access to these data, investors provide value-added services *after* investing, making cross-investor comparisons prone to selection issues. Accelerator programs offer compelling solutions to both of these problems. Structured program designs facilitate systematic data collection on qualitative aspects provided by investors who are unconstrained by prior financial commitments.

One such setting is a global science-based entrepreneurship program ("SEP") for seed-stage startups. SEP is a nonprofit that operates in business schools ("sites") and is steered by senior faculty. The essence of SEP is four in-person "sessions" every eight weeks to help founders prioritize three measurable business objectives to focus on "at the expense of everything else."[3] A fifth and final graduation meeting concludes the program year. Since its inception in 2012, SEP has grown from a solitary business school and 24 alumni, to 13 business schools across seven countries, with 23 specialized technology streams, and more than 1,000 alumni estimated to be worth over $28 billion.

Admission to SEP is competitive and open to startups from anywhere around the world. Candidates are subjected to a rigorous evaluation process that includes submitting a detailed application and participating in business and technical assessment interviews (see Appendix A for more details on the evaluation process). Finalists are offered admission to a technology "stream" at a unique business school "site" (hereafter, stream-site pairs are referred to as "track"). Each stream assembles mentors with relevant domain expertise, such as prior investment history in the same sector. The program year of data analyzed here includes seven specialized technology streams, including AI, space, and quantum computing, and one general stream for startups that do not fit in any of the specialized groups (see Appendix A for the evolution of streams). The matching of startups to tracks is administered centrally by SEP headquarters and is done via the Nobel Prize-winning Gale-Shapley deferred acceptance algorithm.[4]

Data used in this project are from the 2018-2019 cohort–the latest and largest participating cohort available when I began collecting data. There are 148 VC and 44 angel mentors,[5] and 253 startups, representing all 14 site-streams, or tracks. Mentors are predominantly angels and VCs

[3] SEP directors use this phrase when providing instructions to mentors and founders to emphasize that the core purpose of SEP design is to help startups prioritize business objectives.

[4] This algorithm uses two-sided preference rankings to produce stable results. One side of the ranking is provided to SEP HQ by track leads, and the other side is provided by startups.

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

from established ecosystems such as Silicon Valley, Boston, and Toronto, invited to be part of the program based on their reputation in building or investing in high-growth startups. Mentors cannot delegate their role to an associate or employee, so only the formally registered mentors are permitted to participate. Each track has an average of 18 startups (SD = 4.8) and 19 mentors (SD = 6.8), with 75% of mentors participating in a single track, 18% in two tracks, and the remaining 7% in three or more tracks. See Appendix A for additional details on sample construction and attrition.

2.1 Mentoring Process

A week before each session, mentors in each track receive an email from SEP containing updated one-page dossiers on every startup in their track. Figure 1 shows an example. These dossiers outline the founders' proposed objectives for the upcoming eight weeks, the status of the previous finalized set of objectives, as well as time-varying financial details. The document also contains a hyperlink (top-right corner of Figure 1, "Venture Overview") to a longer curated document with further details ranging from target customer and core technology to founders' educational background. The email asks mentors to familiarize themselves with each firm's progress and formulate their feedback on the proposed objectives.

On the morning of session days, founders meet privately with 4-6 mentors from their track to receive one-on-one feedback on their proposed objectives. In the afternoon, each track's mentors and founders convene in distinct large classrooms like the one shown in Figure 2 to debate and reconcile individual mentors' feedback since morning into a final set of objectives. A business school professor moderates these debates one startup at a time until each firm finalizes its objectives (see Appendix A for details on objective design requirements). Sessions conclude in the early evening with deliberations. First, founders are ushered out of the room, and then the moderator asks mentors to raise their hands if they feel equipped to support each venture in achieving its finalized objectives. Appendix Figure B2 summarizes the day using a sample mentor schedule, and Appendix A provides further details on the deliberations protocol.

Mentoring decisions are costly as each obligates a mentor to commit four hours of their *personal time* to the founders of each startup chosen. The modal (average) startup receives one (1.61) mentor, and the modal (average) mentor selects one (1.64) startup. Decisions are also high-stakes for startups

Figure 1: Example of Startup Dossier

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

[redacted]

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

VENTURE DESCRIPTION

[redacted]

CDL JOURNEY

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

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

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

Session 4

PROGRESS ON OBJECTIVES SET AT THE PREVIOUS SESSION

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

PROPOSED 2-MONTH OBJECTIVES

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

CEO UPDATE

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

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

CDL COMMENTARY BY RACHEL HARRIS (VENTURE MANAGER)

1. [redacted]
2. [redacted]

FINANCING UPDATE

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

Notes: This figure shows a sample startup dossier distributed to mentors before sessions. It includes updated objectives, a status update from the CEO, commentary by the SEP manager responsible for the startup, the latest financial information, and a history of main mentor recommendations from prior sessions. Portions that may reveal the identity of the startup or SEP are redacted.

Figure 2: Finalizing Objectives via a Moderated Debate

Notes: This image shows an in-progress discussion in the large room. Founders and mentors engage in a debate moderated by a business school professor (hidden behind the founder) to arrive at a finalized set of objectives for the next eight weeks.

as those without formal support are dropped from subsequent sessions. While I do not directly observe individual off-cycle meetings, SEP has specific design features to ensure mentors spend at least four hours with the startups. For example, a SEP manager responsible for the startup is required to connect the founders with their mentors shortly after the session and facilitate setting up the meetings.[6] Throughout the eight-week cycle, SEP managers touch base with founders to document progress on objectives and provide additional assistance with setting up meetings with mentors if required. Honoring the four-hour time commitment from mentors is also tracked by the managers and enforced by director-level staff. It is still possible that highly diligent mentors go beyond the four-hour time commitment, though I am not aware of any such cases. The cycle ends with founders sending their respective managers a draft dossier for the next session, including proposed objectives for the next period and evidence for any objective marked as complete.

2.2 Mentors

A mentor is an angel if, from January 2018 to December 2019 (8 months before and 8 months after the study cohort), they made a personal investment. A mentor is a VC if they made a partner investment during the same period. Investment histories are from Pitchbook, Crunchbase, press releases, and SEP'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,

[6] SEP managers have expertise in evaluating and supporting early-stage startups, but they are strictly prohibited from giving advice.

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.[7] For educational background, I collect information on the name of alma maters, degree levels (e.g., Master's), and majors (e.g., Bachelor of Commerce).

Table 1 summarizes mentor characteristics. All angels are former founders, and 61% have had an exit, whereas only half the VCs are former founders and one third have an exit. In other words, angels appear to have twice as much operating experience, and this difference is statistically significant. In terms of other types of experience, however, angels and VCs are quite similar. Both have significant managerial experience, with roughly 90% having served in executive positions. They also do not differ significantly in terms of technical (e.g., engineering) and academic (e.g., adjunct professor) jobs held. Educational background is balanced for the majors, and by highest degree earned, except for MBA. Twice as many VCs have an MBA degree. Angels are also older and less likely to be female. Lastly, there is no significant difference in the number of unique startups mentored and the average time spent with each startup.

2.3 Startups

Table 2 describes the 253 startups in my sample. Pre-program information is from startup applications, first session dossiers, and Internet searches. Post-program funding data are sourced from LinkedIn, Pitchbook, Crunchbase, founders, mentors, and news articles. Overall, startups are early-stage, science-based, and run by young first-time founders. In the remainder of this section, I describe the sample in comparison to other published startup samples. This comparison helps assess sample representativeness in the absence of data on the universe of seed-stage, high-technology startups.

The number of founders (2.6) and employees (4.1) is similar to the 2.6 founders and 3.4 employees found in the sample of seed-stage startups in AngelList (Bernstein *et al.*, 2017), and 2.9 founders in the MIT E-Lab startups (Hsu, 2007a). Regarding the development stage, 23% have a prototype when applying to the program, which is close to the 29% of university-based projects

[7] It is not feasible to distinguish successful from unsuccessful acquisitions because purchase amount and terms of acquisitions are mostly undisclosed. Later in presenting the mechanism results, I discuss why this is not a concern for my study.

Table 1: Summary 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
Highest Degree: PhD	0.23	0.42	0.18	0.39	0.51
Major					
STEM	0.61	0.49	0.50	0.50	0.19
Business (Excl. MBA)	0.14	0.35	0.16	0.36	0.76
MBA	0.16	0.37	0.38	0.49	0.01
Demographic					
Female	0.07	0.25	0.22	0.41	0.03
Age	51.59	11.32	46.28	10.84	0.01
Mentoring					
Mentorship Hours Committed	27.91	16.20	22.73	20.64	0.13
Unique Startups Mentored	4.50	3.09	4.07	3.36	0.45

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

Table 2: Summary of Startups

$N = 253$	Mean	Median	Standard Deviation	Min	Max
Panel A: Venture Characteristics					
Founding Team Size	2.55	2	1.22	1	8
Firm Size	4.13	3	5.52	0	50
Has Prototype	0.23	0	0.42	0	1
IPR Patent Important	0.71	1	0.46	0	1
Pre-Program Capital ($000s)	514.04	67	1,523.20	0	20,000
Pre-Program Revenue ($000s)	149.78	0	485.06	0	5,250
External Funding ($Million)	1.24	0	4.40	0	39
Valuation ($Million)	3.78	0	12.79	0	132
Panel B: Founder Characteristics					
Num. PhD Founders	1.04	1	1.22	0	5
Has PhD Founder	0.55	1	0.50	0	1
Mean Founder Age	34.40	32	8.77	19	68
Has Founding Exp.	0.41	0	0.49	0	1
Has Startup Work Exp.	0.42	0	0.50	0	1
Has Female Founder	0.26	0	0.44	0	1

Notes: This table describes the characteristics of startups.

in the U.S. (Jensen & Thursby, 2001). For IP appropriation strategy, startups are similar to SBIR ventures that received R&D funding and the matched venture-backed startups (Gans *et al.*, 2002). Specifically, Gans *et al.* (2002) find a score of 3.5/5 for the importance of patenting. Following their approach, I manually label a binary variable from venture applications where founders describe how they *intend to* protect their IP. 71% state they will do so through patenting, although it is likely that a much lower percentage will file for or be granted a patent–during the 8-month study period, only 13% did.

The median amount of capital raised and revenues generated before joining the program are $67,000 and zero, respectively, reflecting the early stage of the startups in my sample. The mean capital raised before joining the program is approximately USD$370 thousand, which is similar to USD$304 thousand in AngelList startups (Bernstein *et al.*, 2017). Assuming startups were worth close to zero before joining SEP, the three-year step-up in valuation is $2.5 million, which is higher than $2.24 million step-up over eight years in startups that received their first round of VC funding between 2002 and 2010 (Ewens *et al.*, 2018).

Moving to founder characteristics in Panel B, founders are more educated, younger, and less experienced than comparable samples. Half of the teams have at least one PhD founder, twice the startups in MIT E-Lab and MIT Venture Mentoring Services (Scott *et al.*, 2020). The average team age of 34 is lower than the age of 40 found in Ewens *et al.* (2018) and the 2010 Global Entrepreneurship Monitor (Liang *et al.*, 2018), though neither of these samples is constrained to younger seed-stage companies. In terms of experience, 41% of teams have former founders, slightly less than in Ewens *et al.* (2018). Lastly, 26% have at least one female founder, reflecting the documented under-representation of women in tech entrepreneurship (Ruef *et al.*, 2003; Harrison & Mason, 2007).

3 Empirical Approach

At each session, each track's mentors can choose between startups that differ in the business objectives they need help achieving. The statistical analysis compares angels' and VCs' likelihood of providing advice on different business objectives by constructing each mentor's bundle of startup choices. Appendix Table B1 shows the panel structure of data. The estimation strategy models the provision of mentor advice as a function of whether the startup prioritizes experimentation and whether the mentor is an angel or a VC:

$$Advice_{ijt} = \beta_1 Angel_i \times Experiment_{jt} + \beta_2 Experiment_{jt} + \boldsymbol{x}_{jt}\boldsymbol{\beta}_3 + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt}. \quad (1)$$

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

Changes in the growth potential of startups may confound mentoring decisions. So, I add a vector of time-varying financial controls $\boldsymbol{x}_{jt}$ that reasonably summarize growth trajectories. These controls are $RevenuePositive_{jt}$, which equals 1 if the startup is revenue-positive to account for investor risk preferences, $AbvMedFunding_{jt}$, which equals 1 if total funding is above-median to account for round size preferences, and $OpenRound_{jt}$, which equals 1 if the startup has an open funding round to account for immediate deal flow incentives.

The equation is estimated as a linear probability model (LPM) with mentor clustered standard errors to account for error correlation in mentor decision-making. The main coefficient of interest β_1 is interpreted as the percentage point change in the probability of receiving experimentation advice from an angel rather than a VC. Despite the binary nature of the response variable, I use LPM because nonlinear models such as logistic produce inconsistent estimates with multi-way fixed effects due to bias caused by the incidental parameter problem (Kwak *et al.*, 2023).[8] It is possible, however, to use one-way fixed effects with a fixed-effects logit model. I utilize this model to report supplemental results.

4 A Novel Typology of Early-Stage Startup Activities

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

[8] The issue is less severe when there are many observations for each effect (e.g., several startup-mentor observations for each session FE), and significantly more severe when there are few observations for each (e.g., a handful of mentor-session observations for each venture FE).

Figure 3: Typology of Early-Stage Startup Activities

4.0.1 Conceptual Categories

Starting with experimentation, I follow an established literature to define it as tests that create real options concerning product, market, and regulation (Levinthal, 2017; Kerr *et al.*, 2014b; Manso, 2016).[9] This definition is based on the notion of experimentation as an approach to learning under uncertainty, rather than as trial-and-error (Ries, 2011; Blank, 2020), or a method of inference (Koning *et al.*, 2022).

The classical competitive strategy also highlights learning through analysis, whereby entrepreneurs generate options via search and optimize to a decision (Porter, 1980). This approach underlies such theories as discovery-driven planning (McGrath & MacMillan, 1995), multiple opportunity recognition (Shane, 2000), and search (March, 1991). Following this literature, I define Analysis as search and planning activities concerning product, market, and organization (Shane & Delmar, 2004; Delmar & Shane, 2003).[10]

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

The remaining two categories, implementation and resource acquisition, are distinct from the first two in that they are not intended for learning. Implementation refers to the execution of ideas, such as sales, marketing, and product delivery, whereas resource acquisition pertains to the appropriation of financial, intellectual, and human capital. I use these additional categories to benchmark my main results on the mentoring role of investors in supporting deliberate learning.

Table 3 summarizes the key features of these four conceptual categories, and Figure 4 displays the distribution of each category among startup objectives. Interestingly, the median occurrence of categories in top-three prioritized objectives is roughly equal, indicating the balanced importance of the conceptual categories.

[9] 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.”

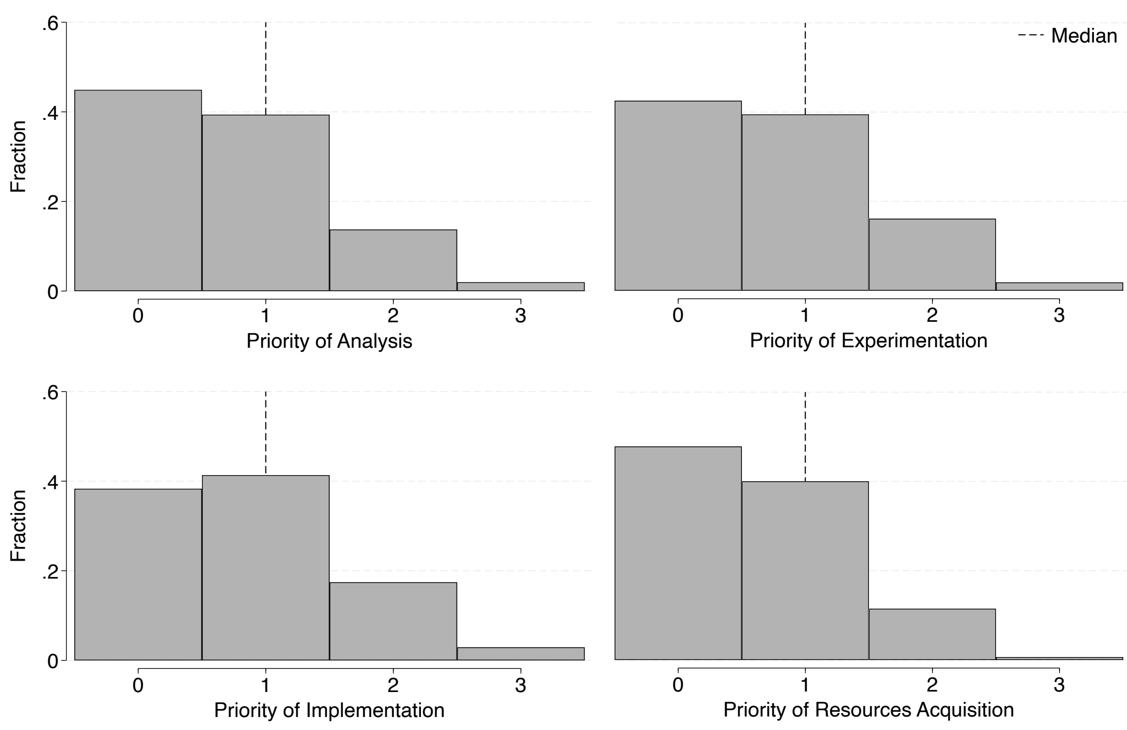
[10] Examples include “identify ten types of crops with the biggest market in North America,” “identify specific beachhead markets,” and “prepare capital forecast for next raise.”

Table 3: Four Conceptual Categories of Entrepreneurial Activity

Category	Features	Examples
Analysis	Commitment-free Standard Templates Noisier than Experimentation	Examine size of the market; Develop product roadmap
Experimentation	Not Commitment-free No Standard Template Less Noisy than Analysis	Validate Technology; Validate Product-Market Fit
Implementation	Involves Selecting Ideas Intent is not Learning	Launch product; Get new customers
Resource Acquisition	Financial Capital Human Capital Intellectual Capital	Raise capital; Hire CEO Submit Patent Application

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

Figure 4: Distribution of the Priority of Conceptual Categories in Startup Objectives



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

4.0.2 Labelling Procedure

Directly labelling thousands of objectives at a conceptual level is prone to cognitive error. To minimize this issue, I adopt an iterative approach to first reduce the dimensionality of objectives to a small set of distinct business functions, then map these functions to the categories described above.

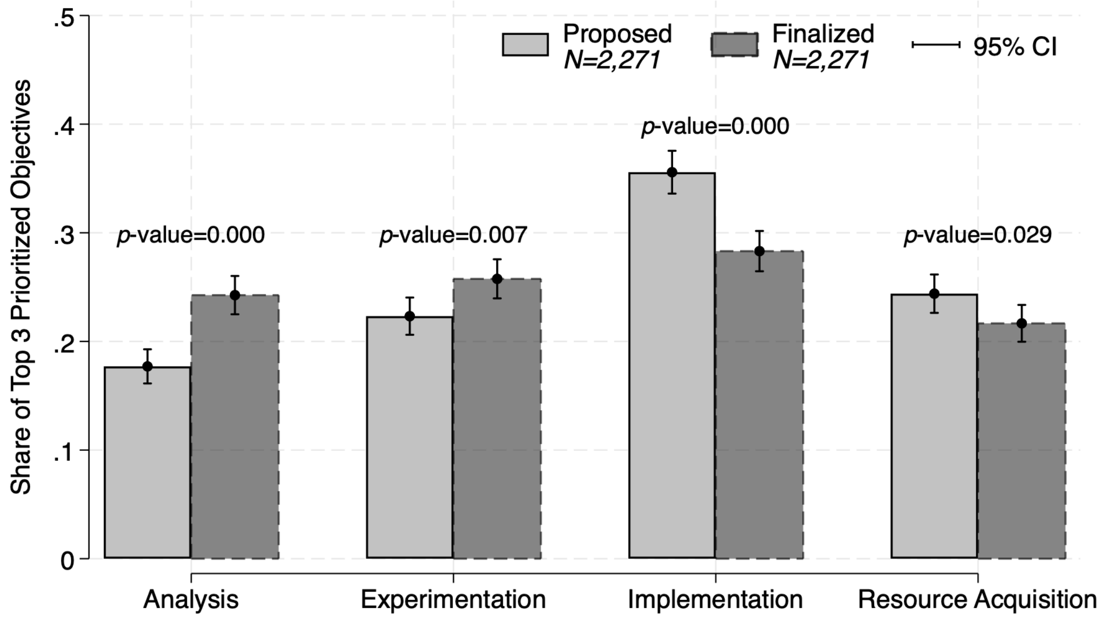
I start by reading each objective and grouping together the ones that are almost identical (e.g., objectives that are about creating a marketing video). This results in many duplicate groups due high clustering sensitivity. Next, I review each group from the smallest (some containing only one objective) to the largest, and merge ones with significant overlap in the core business function (e.g., merge the group for marketing videos with the group on creating marketing brochures). Repeating this exercise two more times, I reach a set of distinct business "activities" that cannot be reasonably reduced without mixing business functions. For validation, three undergraduate students assign a unique label from this final list of activities to the raw text of all objectives, which matches mine 95% of the time. In Appendix Table D9, I catalogue examples and exclusions for each of the activity classes. Finally, based on the definitions developed earlier, I map each activity to a conceptual category, through a coarser level of aggregation that I call "tasks." The mapping is illustrated in Figure 3 by connecting lines.

The classification reveals a novel and interesting fact about the nature of business advice. Figure 5 shows the share of each conceptual category in objectives proposed by founders before the mentoring sessions, and in objectives finalized after revising based on mentor feedback. A pronounced pattern is that, relative to mentors, entrepreneurs significantly under-prioritize learning–analysis and experimentation. The fact that there is a shift in priorities also implies that entrepreneurs take advice seriously, considering also that Figure 5 only shows transfer of priorities across aggregated levels, and not within-class revisions to the objectives (see Appendix Table D10 for proposed and finalized shares across all classification levels).

5 Main Results

Figure 6 previews the main finding that angels are more likely than VCs to provide advice on experimentation, but this is not so for other types of activity. Panel A shows that when experimentation

Figure 5: The Share of Conceptual Activities in Proposed and Finalized Objectives

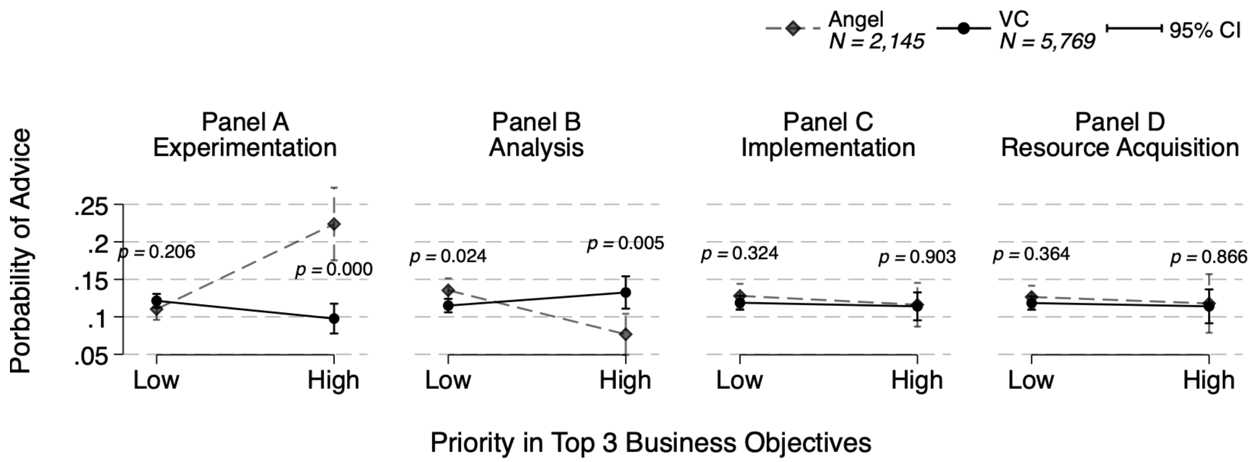


Notes: This figure shows the average share of conceptual categories in the proposed (light color) and finalized (dark color) objectives. The *p*-values are from two-sided difference in means tests.

is not prioritized, angels and VCs are roughly equally likely to provide advice, but when it is prioritized, the probability of angel advice doubles from 0.11 to 0.22. Using an alternative tabulation in Appendix Table B2, the priority of experimentation is 26% higher among angel-mentored startups than VC-mentored ones. Panel B shows that VCs are instead more likely than angels to provide advice on analysis. Panels C and D show no difference in implementation and resource acquisition. While illustrative, these univariate tests do not account for the unobserved qualities of startups and mentors. The multivariate tests below aim to tackle these issues.

Table 4 shows linear probability estimates of Equation (1). Baseline estimates in Column 4-1 show that angels and VCs are indistinguishable in terms of their willingness to provide advice. Similarly, the small and insignificant coefficient for *Experimentation* means that being in an experimentation phase is not predictive of receiving advice. Column 4-2 shows that these estimates are robust to firms' time-invariant qualities. Columns 4-3 to 4-6 show estimates of the main results with progressively restrictive controls. For brevity, I focus on the preferred model shown in Column 4-6, which includes the full set of fixed effects and time-varying controls. The coefficient for the interaction *Angel* $\times$ *Experimentation* is positive, large, and significant. Angels are 14.4

Figure 6: The Probability of Angel versus VC Advice by Activity Type Supported



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

percentage points–over twice–more likely than VCs to provide advice on designing and running business experiments.

I interpret the revealed preference of angels as having a skill advantage in experimentation. However, confounding determinants of mentoring decisions raise alternative explanations. While I examine these explanations in the next section, there is also the immediate concern that the effect is an artifact of the way in which objectives are classified as experimentation. For example, business planning, a pervasive task I categorize as Analysis, may be predicated on product market validation tests, such as surveying potential customers. This raises the question of whether a more flexible definition of experimentation might alter the results. I create two broader alternatives of experimentation by rearranging the links between Activities and Conceptual Categories shown 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}*}*, being cautious that the unobserved context of selecting a target market may also involve product-market fit experiments. Results in Appendix Table B3 show that the main finding is robust to these alternative measures.

It is worth noting that the finding so far should not be interpreted as VCs refusing to drive entrepreneurial learning in general or experimentation in particular. My econometric approach

Table 4: Provision of Experimentation Advice by Angels and VCs

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

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

assesses comparative advantages, not absolute skill levels. As far as entrepreneurial learning is concerned, too, recall that learning and choice also occur via analysis, which is the approach VCs are comparatively more likely to support (see Table B4 for multivariate estimates). In Section 8, I build on this initial finding to create a more complete picture of VCs' skill advantages.

6 Alternative Explanations

I identify four alternative explanations that threaten the skill advantage explanation: 1) deal flow incentives, 2) stage preferences, 3) sorting, and 4) information preferences. Table 5 summarizes the primary tests for each alternative explanation, while Appendix Table B5 provides supplemental tests with additional measures.

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

To evaluate this explanation, I exploit the variation in the capital requirements of startups. Table 5 Column 5-1 and 5-2 run the main specification in sub-samples of startups split by having an open round. The stability of the coefficient of interest indicates that even this sharp change in exposure to deal flow does not change the main result. A worry with this test is that the influence of deal flow incentives affects behavior before rounds open since investor learning starts in anticipation of an impending fundraising. In supplemental tests shown in Appendix Table B5, I find that the results are robust also against expected funding by running results in samples split by median runway. Runway is a metric that uses cash flow and cash burn rate to calculate time remaining before the firm needs to raise capital again.

These results might be surprising: how could competing investors *not* take advantage of mentoring to make better financing decisions? I argue that they do, but not by behaving opportunistically in making mentoring decisions. To the extent investors vary in their deal evaluation abilities, selecting into mentoring based on expertise reveals more information, if information disseminates quickly post mentoring. In SEP, it is unlikely that mentors have incentives to withhold information in a mentoring setting due to reputational costs (see Appendix A for a discussion). However, it is also unclear if they *can*. Startups can have more than one mentor in a given cycle, and most have more than one mentor across cycles. To maximize private information, a mentor needs to collude with others. Even with sufficient incentives to do so, the founders and SEP managers also reveal information, each for different reasons, making it rather challenging for a given mentor to bury signals.

Stage preferences: VCs have a higher presence than angels do in late-stage funding. If experimenting would be less common in later stages, one may worry that the main result is an artifact of VCs' stage preferences. This may be the case even thought the VCs in my sample are either seed-focused or invest dedicated seed funds of larger VCs. For instance, VCs may develop late-stage support specialization that influences their preferences away from mentoring nascent companies

Table 5: Tests of Alternative Explanations

Explanation:	Deal Flow Incentives		Stage Preferences		Sorting		Information Preferences	
DV =	Advice		Advice		Advice		Advised Experiments	
	(5-1)	(5-2)	(5-3)	(5-4)	(5-5)	(5-6)	(5-7)	(5-8)
Sample:	No Open Round	Open Round	BlwMed Funding	AbvMed Funding	Full Sample	Full Sample	Feedback Sample	Feedback Sample
Angel × Experimentation	0.128^{***}	0.115^{***}	0.129^{***}	0.171^{***}	0.116^{***}	0.102^{***}		
	(0.032)	(0.040)	(0.036)	(0.049)	(0.028)	(0.032)		
Matched					0.351^{***}	0.356^{***}		
					(0.028)	(0.029)		
Angel × Matched					0.065	0.043		
					(0.056)	(0.059)		
Matched × Experimentation						−0.026		
						(0.068)		
Angel × Matched × Experimentation						0.109		
						(0.105)		
Angel							−0.021	−0.066
							(0.064)	(0.068)
Proposed Experiments							0.566^{***}	0.538^{***}
							(0.062)	(0.058)
Angel × Proposed Experiments								0.077
								(0.096)
N	3,899	4,015	4,413	3,497	7,914	7,914	411	411
Startup FE	X	X	X	X	X	X	X	X
Mentor FE	X	X	X	X	X	X		
Session FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X

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

for reasons unrelated to their experimentation skills.

Results in Columns 5-3 and 5-4 rule out this explanation by running the main specification in sub-samples split by median capital raised up to a session as an indicator of funding stage. To account for heterogeneity in capital intensiveness across technologies, I calculate median funding within technology verticals. Supplemental results in Appendix Table B5 show a similar pattern using alternative measures of stage based on revenue stage, product development stage, and age since incorporation. An interesting pattern is that the angel effect is larger for more mature startups. Although this difference is not statistically significant, it aligns with the skill advantage explanation. Insofar as experiments are more complex in later than in earlier stages, angels' skill advantage plays a more salient role in more mature companies.

Sorting: Investors are more likely to fund startups that they know (Sorenson & Stuart, 2001; Hochberg *et al.*, 2007). This would be problematic if, due to assortative matching or network effects, angels are more familiar than VCs with startups in an experimentation phase. To examine this hypothesis, I exploit variation in mentors' private meetings before mentoring decisions are made. Specifically, I codify the indicator *Match* that equals 1 if a given mentor had a private meeting with a startup in the morning of the session day. The coefficient for *Match* in Column 5-5 shows, as expected, prior familiarity does predict mentoring decisions, but the coefficient for the interaction shows that this effect does not differ by investor type. Column 5-6 goes one step further to show that familiarity does not change angels preference for mentoring experiments.

Information preferences: The last possibility considered is that angels have a *taste* for experimentation. For instance, they may view experimenting as more informative for early-stage startups than analysis. If true, then angels should also advise startups to prioritize experiments more than VCs do. I test this hypothesis by codifying transcribed notes from the one-on-one meetings where mentors tell startups which objectives they should prioritize.

The specification here is to regress the number of experiments advised to the same startup by different mentors. Column 5-7 shows that angels and VCs are quite aligned in their judgment about the priority of experimentation. However, the insignificant effect on *Angel* can be due to high-experiment-proposing founders being ex-ante matched with angels more frequently than they are matched with VCs. Column 5-8 eliminates this concern by adding the interaction *Angel* $\times$ *Experiments*, showing that angels and VCs are in agreement about how much experimentation the startup should do even after the proposals. Appendix Figure B4 shows visual evidence that angels and VCs are in fact aligned across all activity types. In supplemental tests, Appendix C shows that the main results are also robust to homophily in mentoring decisions.

7 Mechanism: Learning-by-Doing

This section provides three sets of evidence supporting the hypothesis that experimentation is a skill developed via learning-by-doing, and angels have a skill advantage in that domain due to having more operating experience than VCs. First, I show the main result that angels provide more experimentation advice is driven by angels who have substantial operating experience. Second, I find that the experience channel is only salient in less experienced founding teams, and only for experimentation, not for other types of activity. Third, the underlying role of operating experience becomes more salient when I raise the threshold for capturing experimentation skills from selecting into advice, to success in achieving the objectives advised.

To begin, I collect data on whether each founder and mentor has operating experience. As predicted by prior studies (Ibrahim, 2008; Linde *et al.*, 2000), all angels in my sample are former entrepreneurs, leaving no variation to assess heterogeneous response with respect to founding history. This is not a huge loss, however, since founding history alone is a noisy measure for the extent of one's operating experience. The founder of a boutique consulting firm acquires different skills than the founder of a scalable startup, and the latter has less experience than one who grows their firm to a mature stage. For these reasons, I use exit as a clear market-based threshold for substantive operating experience. A mentor is exited if their company was acquired or was taken public. Note that not all acquisitions are successful because the company may be bought at less than the cumulative value of all investments. This is not an issue because the phenomenon of interest here is not success, but exit as an indicator for meaningful experience. To the extent exit places a lower bound for entrepreneurial effort, it proxies for meaningful operating experience more accurately than one's claim to have founded a company. The shortcoming of exit, however, is that it likely underestimates experience for operators who fall just below the exit threshold.

Table 6: Operating Experience and Provision of Experimentation Advice

	Sample of Angel Decisions		Sample of VC Decisions	
DV = Advice	(6-1)	(6–2)	(6–3)	(6–4)
Exit:	Yes	No	Yes	No
Experimentation	0.095**	0.052	–0.043	–0.034*
	(0.042)	(0.044)	(0.028)	(0.020)
N	1,158	908	2,056	3,698
FEs & Controls	X	X	X	X

Notes: This table shows the likelihood of providing experimentation advice in sub-samples of angels and VCs split by exit history. Controls and fixed effects used are identical to the main specification in Column 4-6 of Table 4. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

Table 6 shows the change in the probability of receiving experimentation advice in samples conditioned by experience and investor type. Comparing Columns 6-1 and 6-2 shows that only exited angels are significantly more likely to provide advice on experiments than on other activity types. Similarly, for VCs, comparing Columns 6-3 and 6-4 shows that VCs' lack of interest in mentoring experiments is only salient among non-exited VCs. It is puzzling that we do not see a positive experience effect for VCs as we do for angels. One explanation is that the shortcoming of exit described earlier is more severe for VCs because they are less likely to have pursued an entrepreneurial career in the first place. This motivates further examination of the experience mechanism, which I now turn to.

7.1 Founder Experience

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

$$
\begin{aligned}
Advice_{ijt} = {} & \beta_1(Experiment_{jt} \times MentorExpr_i \times TeamExpr_j) \\
& + \beta_2(Experiment_{jt} \times MentorExpr_i) + \beta_3(Experiment_{jt} \times TeamExpr_j) \\
& + \beta_4(MentorExpr_i \times TeamExpr_j) + \beta_5 Experiment_{jt} \\
& + \gamma_i + \delta_j + \eta_t + \epsilon_{ijt}
\end{aligned} \tag{2}
$$

where $MentorExpr_i$ and $TeamExpr_j$ are indicators for mentor and founding team experience. This model is identical to Equation (1) except for the addition of $TeamExpr_j$.

Figure 7 visualizes the estimates of interest. The two left graphs measure mentor experience using exit; the right graphs measure it as prior founding history. The top two graphs measure team experience as prior founding history; the bottom graphs measure it as startup work experience. The top estimates in each subgraph show whether experienced mentors provide more experimentation advice than inexperienced mentors to teams without any startup experience (β_2), and the bottom estimates show this for teams with startup background ($\beta_1 + \beta_2$).

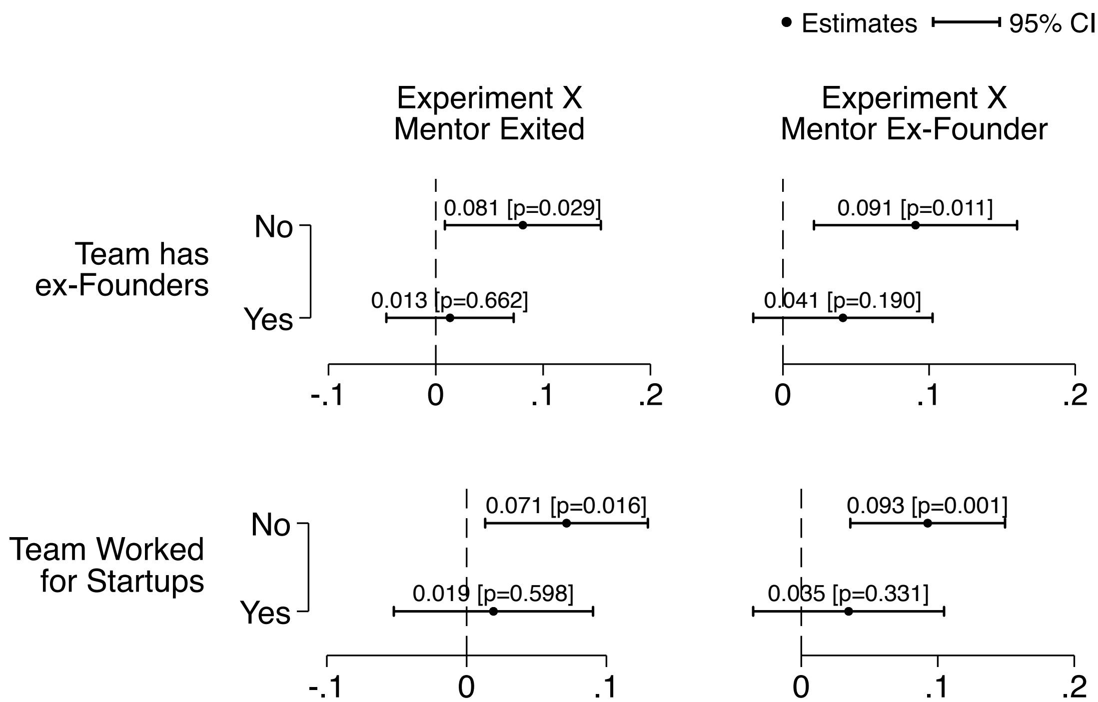
Across the board, experienced mentors provide more experimentation advice, but only to inexperienced teams. Appendix Figure B3 replicates this graph for the remaining conceptual categories, showing that the result only holds for experimentation and not other activity types. This evidence supports the learning-by-doing mechanism and suggests that the experience effect is not driven by broader substitution in mentor-mentee human capital stocks.

7.2 Advice Quality

If experience drives experimentation skills, it should also lead to more effective advice. To measure the quality of advice, I use accurate information on whether the startup achieved each of its objectives. Completion is an appropriate measure of advice quality for three reasons. First, the completion reports are accurate.[11] Second, as Hellmann & Puri (2002) show, advancing firm development is a core investor value-added–the firm must *execute* for investors to make returns. Second, timely execution is also a benefit founders seek in "smart money" resources are unlocked

[11] First, SEP managers are responsible for verifying evidence of completion before releasing dossiers to mentors. Second, founders have strong incentives to be truthful in reporting. Both SEP managers who keep abreast of progress on objectives and current mentors can reveal false completion claims during the next session.

Figure 7: Heterogeneity of Experimentation Advice by Founder and Mentor Experience



Notes: This figure plots estimates from Equation (2). The top estimate in each subgraph is for β_2: the marginal difference in providing experimentation advice by experienced mentors to inexperienced founding teams. The bottom estimate in each subgraph is for $\beta_1 + \beta_2$: the marginal difference in providing experimentation advice by experienced mentors to experienced founding teams. The p-values for the significance of each estimate is also reported.

in stages of the milestones achieved. If feedback by multiple experts approximates true startup priorities better than random chance–a quite reasonable assumption–then variation in objective completion contains information about the effectiveness of advice.

The empirical analysis compares the likelihood of completing different tasks as a function of mentor characteristics. A challenge of using completion to detect advice quality is that tasks are highly heterogeneous in difficulty (consider the difference in preparing a hiring plan versus hiring an employee). This is problematic in my selection framework because specialization in a domain should lead to selecting on tasks that are less obvious to achieve. To make matters worse, the same task also has cross-startup variability in difficulty. For example, the difficulty of obtaining regulatory validation (relative to other tasks) is higher for therapeutics than for medical device companies. Fortunately, objective-level data allows me to account for these issues using task-startup fixed effects. Specifically, I estimate the following model

$$Completion_{ijst} = \beta_1 Angel_i \times Experiment_{jst} + \beta_2 Experience_i \times Experiment_{jst} + \gamma_i + \delta_{js} + \eta_t + \epsilon_{ijst} \tag{3}$$

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

Table 7 shows the results. The first four columns show OLS estimates of Equation (3) for four different measures of experience. Only prior operating experience proxied by exit is associated with a large and significant increase in the rate of completing experiments compared to other types of activity. Interestingly, the $Angel \times Experimentation$ coefficient is positive but insignificant (p-value = 0.462). Before discussing why we do not observe a significant angel effect I consider a key endogeneity threat.

Being a former entrepreneur, particularly an exited one, strongly predicts one's *choice* to become an angel investor.[12] In fact, despite their similarities, angels and VCs also differ in terms of age and business education. Therefore, it is plausible that angels and VCs follow different career paths,

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

Table 7: Quality of Experimentation Advice

	Unweighted				IPTW			
DV = Completion	(7–1)	(7–2)	(7–3)	(7–4)	(7–5)	(7–6)	(7–7)	(7–8)
Experience Measure:	Exit	Executive	Academic	AbvMed Age	Exit	Executive	Academic	AbvMed Age
Experienced × Experimentation	0.037**	−0.024	0.007	−0.009	0.047***	0.003	0.034	−0.008
	(0.017)	(0.037)	(0.051)	(0.017)	(0.011)	(0.031)	(0.053)	(0.020)
Angel × Experimentation	0.024	0.030	0.030	0.031	0.006	0.005	0.007	0.006
	(0.032)	(0.028)	(0.030)	(0.028)	(0.026)	(0.023)	(0.024)	(0.023)
N	2,393	2,393	2,393	2,393	2,393	2,393	2,393	2,393
Mean of DV				0.565				0.561
Mentor FE	X	X	X	X	X	X	X	X
Session FE	X	X	X	X	X	X	X	X
Startup × Task FE	X	X	X	X	X	X	X	X

Notes: This table shows results from regressing completion status of objectives on investor type and experience. Two-way standard errors clustered by mentor and task are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

which biases my results if career trajectories influence one's suite of business skills.

Endogeneity due to career choice is a common issue that has spun a large body of work employing matching methods, particularly inverse probability of treatment weighting (IPTW), to attenuate bias. For example, in assessing the effect of patenting on academic productivity, Azoulay *et al.* (2009) use IPTW to account for the fact that patenters and non-patenters follow different publication trends. More recent work on accelerators by Hallen *et al.* (2020) uses the same method to account for startup selection into accelerators. Building on insights from these prior implementations of IPTW, I exploit mentors' detailed career and educational histories to account for selection into angel investing. The intuition behind IPTW is that a pseudo-population is created by re-weighting each observation inversely proportional to the probability that their background would have led them to choose angel rather than institutional investing. For instance, as being an exited entrepreneur is highly predictive of becoming an angel, ceteris paribus, exited-angel observations are significantly weighted down, and exited-VC observations are significantly weighted up.

Columns 7-5 to 7-8 replicate unweighted estimates with IPTW. Column 7-5 shows that exit estimates become meaningfully larger and more precise. Conversely, comparing unweighted and weighted estimates for the interaction with angel shows a large drop in the point estimate. In Appendix C, I further show that both weighted and unweighted results are robust to determinants of homophilous selection. An interesting result here is that mentoring relationships that are more likely to match on race are associated with poorer completion outcomes. One explanation raised by Bengtsson & Hsu (2015) is that homophily may lead to looser monitoring.

In sum, the learning-by-doing explanation is strongly supported, though it is puzzling that we do not see a significant angel effect since all angels are former entrepreneurs. One explanation is that driving success in execution requires a larger wedge in business skills, which is captured by the level of experience encoded in exit. A second explanation is that the strength of the correlation between founding history and exit swamps the effect of non-exited operators.

Predictiveness of Completion: Is completing experiments predictive of entrepreneurial finance outcomes? Because SEP mentors are from top investors whom startups would pursue for funding, one test of predictiveness is whether experimentation increases the precision of investor beliefs about startup quality. To measure belief precision, I code an indicator that equals 1 if the startup is dropped immediately after the first period (i.e., immediate shutdown) or conditional on surviving, never gets dropped. In other words, mentor beliefs would be less precise if, after eight weeks of mentoring the startup, they think the firm is good enough to continue receiving costly mentoring resources but later change their minds and drop the venture anyway. The statistical approach then regresses this outcome on the types of activity attempted and completed since the first session.

Across multiple specifications, completing experiments predicts better beliefs, but this is not the case for analysis, implementation, and resource acquisition. In terms of magnitudes, completing an extra experiment is associated with a 14.2-15.1% increase in immediate shutdown or full survival rather than intermediate shutdown. The full set of results is displayed in Appendix Table B6.

8 The Advantage of VC Advice

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

Table 8 Column 8-1 shows the baseline result that VCs are more likely to provide advice on analysis. Column 8-2 shows that this difference remains directionally unchanged across all tasks constituting analysis, though it is only significant for business planning. To probe the structure explanation, I start with experimentation, recognizing fact that experiments also vary in the degree to which they contribute to organizational structure. Column 8-3 shows that the angel effect is positive and significant across all experimental tasks except for regulatory validation.[13] This is interesting and suggestive of VCs' specialization in establishing structure if we take the view that sound legal infrastructure is an organizational building matter.

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 labelling effort–instead, I simply aggregate actions from the left column of Figure 3 that correspond to organization building. The relevant actions identified include business planning, establishing sales processes, building production capability, forming partnerships, obtaining regulatory approval, hiring, licensing and fundraising (denoted in Figure 3 by $\{t_2, a_{19}, a_{20}, a_{21}, a_{22}, a_{28}, t_{10}, a_{33}, a_{34}\}$). The indicator *Org. Development* then equals 1 if at least two of the three prioritized objectives are in that category.

Column 8-4 shows that VCs are 48% more likely than angels to drive organizational development, consistent with the idea that professionalization is a mark of VC intervention. In Column 8-5, I add the analysis category back as a covariate, and find that estimates for both analysis and organizational development remain pretty stable compared to their baselines. This suggests that VCs drive entrepreneurial learning via analysis more than angels do, in addition to providing more advice on organizational development.

[13] Regulatory validation pertains to the fairly homogenous operation that entails producing evidence for the viability of a regulatory pathway. This is usually done via meeting with regulatory experts (see Appendix Table D9 for details and examples of this task).

Table 8: Heterogeneity of Advice & VC Specialization in Establishing Organizational Structure

DV = Advice	(8-1)	(8-2)	(8-3)	(8-4)	(8-5)
Analysis	0.020				0.020
	(0.015)				(0.015)
Angel × Analysis	−0.078***				−0.075***
	(0.021)				(0.022)
Analytical Tasks					
Angel × Market Product Research		−0.011			
		(0.022)			
Angel × Planning (Financial, IP, Sales, Reg.)		−0.034**			
		(0.015)			
Angel × Product, Technology Roadmap		−0.055			
		(0.037)			
Experimentation Tasks					
Angel × Product Market Fit Validation			0.045**		
			(0.018)		
Angel × Technology Validation			0.079***		
			(0.020)		
Angel × Regulatory Validation			−0.041		
			(0.060)		
Organizational Development					
Org. Development				0.009	0.009
				(0.012)	(0.012)
Angel × Org. Development				−0.057***	−0.055***
				(0.018)	(0.018)
N	7,914	7,914	7,914	7,914	7,914
Mean of DV					0.120
FEs & Controls	X	X	X	X	X

Notes: This table examines the heterogeneity of angel versus VC advice across different types of activity. *Org. Development* in Columns 8-4 and 8-5 is an indicator that equals 1 when at least two of the startup's priorities are on business planning, establishing sales and production processes, forming partnerships, hiring employees, licensing, and raising capital. Put differently, this variable equals 1 if the startup's top-three priorities include two or more of the following labels described in Figure 3: $\{t_2, a_{16}, a_{19}, a_{20}, a_{21}, a_{22}, a_{28}, t_{10}, a_{33}, a_{34}\}$. Standard errors clustered by mentor are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

9 Discussion

How do two of the largest suppliers of risk capital to early-stage startups, angel investors and venture capitalists, differ in the firm development support they provide to young startups? This paper shows that an important difference is in their provision of advice.

The findings reveal that compared to VCs, angels are more likely to provide experimentation advice. I also present evidence that angels have a skill advantage in experimentation because they have learned how to run effective experiments by practice, via developing and growing their own entrepreneurial ventures. To tackle a key endogeneity concern due to mentors' private incentives, I show that my results do not change as startups' current and expected capital requirements change sharply. The detail in the data also allows me to test and rule out other alternative explanations based on heterogeneous information preferences, stage preferences, and sorting.

This study offers new insights into our understanding of investor strategy, especially in selecting and supporting their portfolio firms (Baum & Silverman, 2004). Shepherd (1999) shows that risk investors prioritize the firm's capability to learn and grow, while Aggarwal *et al.* (2015) show that the quality of this evaluation itself depends on the ability of the investor to ascertain firm quality. I extend these insights by suggesting a broader fit between investment strategy and dynamic capabilities, whereby investors anticipate the effectiveness of their value-added potential in making funding decisions. For instance, the fact that older VC funds invest in later-stage firms (Barrot, 2017) can be explained by diminished mentoring capacity due to existing commitments to portfolio ventures. A related implication is for the enduring puzzle that angels obtain weaker control rights than VCs despite investing in presumably riskier deals (Dessein, 2005). My results provide the testable explanation that hands-on involvement may mitigate moral hazard problems, thus reducing the need for formal control provisions (Holmstrom, 1979). For example, high influence on early-stage experiments can provide informal control over the firm's strategic decisions that substitute formal control instruments.

This paper also offers new research directions for understanding the role of venture capital in entrepreneurial strategy. The distinction between angels and VCs in preferences for driving experimentation versus organizational infrastructure is reminiscent of the essential complementarity between idea and execution. Thus, studies that explore the complementarities between angels and

VCs (such as Hellmann *et al.*, 2021) may find new explanatory power in studying investors' value-added services. Such research can guide models of the equilibrium dynamics between angels and VCs to incorporate non-financial services in their theories (e.g. Hellmann & Thiele, 2015). This project also offers future research opportunity based on Hsu (2004) who shows that entrepreneurs accept lower valuations to associate with more reputable investors. If investors vary sufficiently significantly in the provision of support services, founders may *over*-pay for affiliation if they over-estimate the immediate legitimization benefits compared to the gradual and long-term benefits of business mentoring.

In considering the determinants of startup-investor matching, my setting only allows me to observe investors' choices of startups and not vice versa. This is a point of departure from how the entrepreneurial finance market works, but it also serves to help isolate investor preferences. Assortative matching in financing decisions (Sorensen, 2007) has plagued most empirical studies in venture capital and may be responsible for some of the mixed findings. For example, while studies agree that coethnicity between VC partners and founders is highly predictive of investment decisions, Hegde & Tumlinson (2014) find a positive correlation between ethnic proximity and startup performance, while Bengtsson & Hsu (2015) find a negative correlation. In this regard, accelerators such as SEP may offer needed research design controls to disentangle investor-driven from founder-driven parameters of sorting dynamics.

As the final remark, I note two limitations of this study. First, it is difficult to accurately compare the representativeness of my startup sample to the population of high-technology startups. While I mitigate this concern by comparing the characteristics of my sample to several other samples and settings of U.S.-based high-technology startups, such a comparison is not a definitive test of representativeness. Second, establishing a causal relationship between mentor type and business advice requires randomly varying startups' business objectives. This is impossible, so I employed various econometric techniques, including fixed effects, sub-sample analyses, robustness to alternative measures, tests of alternative explanations, and matching methods to alleviate endogeneity concerns. While these efforts dramatically reduce endogeneity concerns, they do not remove its possibility.

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