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

Amir Sariri

Purdue University*

March 20, 2023

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. I also provide evidence that is inconsistent with alternative explanations, including financial incentives and selection.

* I am indebted to Ajay Agrawal, Joshua Gans, and Avi Goldfarb for their invaluable guidance. For their insightful feedback, I thank Victor Bennett, Kevin Bryan, Susan Cohen, Alberto Galasso, Alfonso Gambardella, Brent Goldfarb, Gary Dushnitsky, Benjamin Hallen, Mitchell Hoffman, Aseem Kaul, Peter Klein, Shannon Liu, Hong Luo, Kristina McElheran, Ramana Nanda, Luis Rios, and Scott Stern as well as numerous conference and seminar participants. I acknowledge support from Canada's Strategic Innovation Fund and Borealis AI. I am deeply grateful to Creative Destruction Lab (CDL) and its staff members for supporting the construction of the database used herein. Special thanks in memoriam to my deceased colleague Dr. Peter Wittek for his unwavering support.

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, but they differentiate themselves by the promise of their post-funding services such as advice (Hsu, 2004).[1] Particularly in the earlier stages, the extensive mentoring role of investors can be instrumental in setting a path to success (Kaplan & Strömberg, 2004; Kerr *et al.*, 2014a; Bernstein *et al.*, 2016). However, investor advice has to date been difficult to observe and measure, so it is unclear how the two competing sources of risk capital differ in this important dimension of value-added services. This has also caused the theoretical literature to make conflicting assumptions about the value-added potential of angels versus VCs.[2] The present paper is the first to address this issue using a rich hand-collected panel of mentoring decisions made by a group of angels and VCs who support early-stage high-tech startups on achieving specific business objectives.

My empirical analysis focuses on the mentoring role of investors in helping entrepreneurs "learn how to learn" (Nelson, 1997). Early on, entrepreneurs are prone to making mistakes regarding uncertain strategic options that are costly to reverse (Eisenhardt & Schoonhoven, 1990). To overcome this problem, a significant literature has emphasized experimentation as an effective method of learning under uncertainty (Kerr *et al.*, 2014b; Nanda & Rhodes-Kropf, 2017; Manso, 2016).[3] However, experiments also entail non-trivial costs, such as partial commitments that foreclose the option to abandon bad ideas (Gans *et al.*, 2019), or conversely, the potential to nudge high-impact ideas toward incremental innovations (Felin *et al.*, 2019). Recent theory by Agrawal *et al.* (2021) argues that these nuanced consequences of experimentation create a particular role

[1] A 2009 OECD report estimates the size of the VC market in the U.S. and Europe at $18.3 and $5.3 billion, respectively, and that of the angel market at $17.7 and $5.6 billion, respectively. This is consistent with the later OECD report (2011), and estimates by Mason & Harrison (2002), and Sohl (2003). The recent proliferation of micro VCs that specialize in seed-stage rounds may be indicative of intensifying competition with angels over smaller and earlier-stage rounds (Amore *et al.*, 2022).

[2] For example, 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 (Leshchinskii, 2003; Schwienbacher, 2009; Casamatta, 2003). This is similar to the conflict present in the regulatory guides and the popular press. For instance, the SEC (2022) emphasizes 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).

[3] Experimentation enables learning about the distribution of payoffs without fully committing the firm's limited resources to a single path (Aghion *et al.*, 1991).

for mentors who can help entrepreneurs design and run informative experiments. New RCT evidence by Camuffo *et al.* (2020) supports this idea by showing that experimentation advice can indeed improve founders' strategic decisions, which squares 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).

The importance of advice to early firm development on the one hand, and the fact that angels and VCs compete by providing a bundle that includes both capital and advice on the other, motivate the research questions that I explore in this paper: are there systematic differences in the type of advice that angels provide compared to VCs? If so, then why do they differ?

To explore these questions, I hand-collect a panel of 7,914 mentoring decisions made by 192 VCs and angels to help a sample of early-stage, high-tech startups achieve more than two thousand measurable business objectives. The setting is a world-leading science-based entrepreneurship program ("SEP") with over $20 billion of equity value created by its participating startups. 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 prioritized objectives over the next period.

The empirical analysis investigates changes in startup objectives over time to explain variation in the mentoring decisions of angels versus VCs. To distinguish different types of business objectives, I develop a novel typology of startup activity using an innovative labelling procedure that is systematic and replicable. To tackle obvious endogeneity concerns, I start by using startup and mentor fixed effects, which focus the analysis on changes in the same mentor's willingness to provide advice to the same startup as its business priorities change over time. The detail in data allows me to also control for time-varying features of startups that may systematically influence the mentoring decisions of angels versus VCs. Further, I examine several alternative explanations based on mentor financial incentives, sorting, information preferences, and startup stage preferences. Lastly, I report robustness of the results against a battery of alternative specifications and measures of experimentation.

I find that angels are significantly more likely than VCs to choose to mentor founders who need support on how to achieve their experimentation objectives (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, hiring). Startups are also more likely to complete their experimental objectives when mentored by angels than VCs. This result does not mean, however, that VCs are less helpful or less likely to support learning objectives. VCs commit a similar amount of mentoring time as angels do, but they are more likely than angels to help founders learn via *analysis* (e.g., financial planning, competitive analysis). Analysis–optimizing to a decision by market research and business planning–is the central approach to decision-making in the classical competitive strategy and in a strand of entrepreneurship literature. (Porter, 1980; March, 1991; Shane, 2000; Delmar & Shane, 2003; Shane & Delmar, 2004). In my sample, too, analysis is just as pervasive as experimentation among startups' prioritized objectives, which suggests angels and VCs play complementary mentoring roles.

Why do angels and VCs differ in their provision of advice? In terms of the experimentation effect, I report evidence consistent with the hypothesis that angels have a skill advantage in that domain due to having more operational experience. Recent work by Gompers & Mukharlyamov (2022) finds that only 7% of all VCs possess substantive entrepreneurial experience, in contrast to angels who are predominantly seasoned entrepreneurs (Ibrahim, 2008; Linde *et al.*, 2000). This interpretation of my main finding is based on the assumption that experimentation is a skill that is developed via learning-by-doing (Gans, 2018) supported by the evidence that entrepreneurial experience endows superior learning practices, such as those concerning product design and target market decisions (Gompers *et al.*, 2010; Goldfarb & Xiao, 2011; Gruber *et al.*, 2008).

These results advance the argument that investors choose to mentor startups that better fit their capabilities, which might explain the puzzle that angels are very 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 experience as operators. This is consistent with the observation that VCs who are experienced ex-founders provide higher post-investment value (Gompers & Mukharlyamov, 2022).

To further explore the learning-by-doing explanation, I show that angels' experimentation effect is only salient among less experienced founders, but VCs' analysis effect does not vary with the experience of the founding teams. This suggests that simple substitution effects in the mentor-mentee entrepreneurial tenure does not explain my results. It also suggests that learning-by-doing explanation does not extend to analysis. To the extent that business analysis is governed by standard market research and planning practices, VCs' analysis effect aligns with their role as professional investors. VCs are known to develop specialized industry knowledge and connections (Sahlman, 1990; Norton & Tenenbaum, 1993; Gupta & Sapienza, 1992), keep abreast of the latest market developments (Metrick & Yasuda, 2010), and practice financial and strategic planning as their core responsibility (Kaplan & Strömberg, 2004; Gorman & Sahlman, 1989)–all parameters that are critical to business analysis and planning.

The foremost contribution of this paper is to overcome empirical challenges concerning measuring and analyzing advice. In doing so, I shed light on the prominent mentoring role of investors (Kaplan & Strömberg, 2004; Sahlman, 1990; Gorman & Sahlman, 1989), and add to our understanding of the link between investor human capital and early firm development (Sørensen, 2007; Hochberg *et al.*, 2007; Barrot, 2017; Gompers & Mukharlyamov, 2022). By comparing angel versus VC advice, 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). Lastly, by virtue of the setting, this paper joins a growing literature on design characteristics of startup accelerators and their impact on regional economies (Hallen *et al.*, 2020; Hochberg, 2016; Cohen *et al.*, 2019a; Cohen & Hochberg, 2014).

Founders who pursue external investors not just to fund their projects, but also to learn how to institute a business may find more value in angels if they need to validate their core idea, while those on a path to scale their firms may find VCs' support more relevant (see Hellmann & Puri, 2002, 2000). The present study also speaks to the popular use but 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). My results suggest that such incentives alone may overlook valuable and nuanced investor human capital that can shape early firm development.

2 Setting and Data

The setting is a world-leading science-based entrepreneurship program ("SEP") for seed-stage startups. SEP is a nonprofit that operates in several business schools ("sites") across North America, Europe, and Asia. I hand-collect data from its 2018-2019 cohort, which includes 148 VC mentors and 44 angel mentors, and 253 startups. Startups are admitted through a competitive process that requires submitting an exhaustive application and participating in interviews. Admitted startups join a unique site and technology "stream" that assembles specialized mentoring resources with relevant expertise (e.g., quantum computing, space launch and propulsion). Mentors are predominantly sought-after angels and VCs from vibrant ecosystems such as Silicon Valley, Boston, and Toronto. Sample construction and attrition are in Data Appendix A.1.

Mentoring is focused on helping founders prioritize and achieve three measurable business objectives. Objectives are designed at four mentoring "sessions" that are held eight weeks apart, along with a fifth graduation session. During the week prior to each session, mentors receive a dossier for each startup such as in fig. 1 to prepare feedback to each startup. This dossier shows founders' proposed objectives, progress on past objectives, and other essential updates.

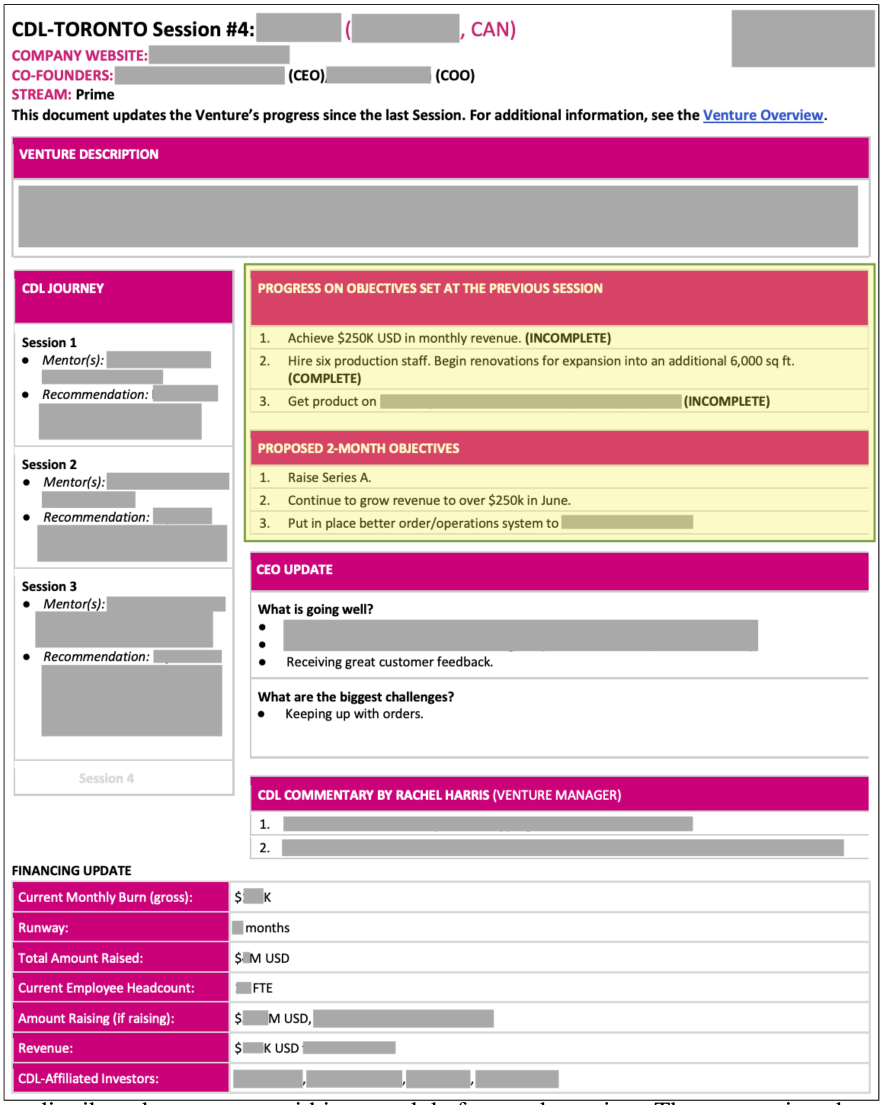
Each startup's objectives are finalized via a debate between all mentors and founders in a room like that shown in fig. 2, moderated by a business school faculty. Once all startups finalize their objectives, entrepreneurs leave the room and mentors decide which ones they wish to help achieve their prioritized objectives by committing to spend at least four hours of their personal time with each chosen startup.[4] Startups that do not receive at least one mentor are dropped from subsequent sessions.

table 1 summarizes the characteristics of the mentors. There are roughly three times as many VCs as angels.[5] Both in terms of founding experience and entrepreneurial success, angels are twice as experienced as VCs, but they are fairly similar in the number of startups they mentor and the average time they commit to each. Data Appendix A.2 describes in detail how I collect data on the type and prior experience of mentors.

table 2 summarizes the 253 startups in my sample. Overall, startups are early-stage, science-based, and run by young first-time founders. There are roughly 2.5 founders and 4 employees per firm. Most startups are deep-tech, with 70% selecting patenting as their primary IP protection strategy. Median funding and revenues are \$67,000 and zero, reflecting their early stage. The average pre-money valuation three years after SEP is \$2.2 million. Since empirical evidence on the universe of technology startups is scarce, it is not possible to directly examine the representativeness

[4] This is significant compared to the time investors spend with their portfolio companies (Gorman & Sahlman, 1989).
[5] The relative scarcity of angels is consistent with other settings such as pitch competitions (e.g., Howell, 2020).

Figure 1: Sample Startup Dossier



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

COMPANY WEBSITE: [redacted]

CO-FOUNDERS: [redacted] (CEO), [redacted] (COO)

STREAM: Prime

This document updates the Venture's progress since the last Session. For additional information, see the Venture Overview.

VENTURE DESCRIPTION

[redacted]

CDL JOURNEY

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

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

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

Session 4

PROGRESS ON OBJECTIVES SET AT THE PREVIOUS SESSION

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

PROPOSED 2-MONTH OBJECTIVES

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

CEO UPDATE

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

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

CDL COMMENTARY BY RACHEL HARRIS (VENTURE MANAGER)

1. [redacted]
2. [redacted]

FINANCING UPDATE

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

Notes: Dossiers are distributed to mentors within a week before each session. The top section shows the status of the finalized objectives from the previous session, and proposed objectives for the next eight weeks.

Figure 2: Group Feedback Meetings

Notes: Each startup's founders meet all mentors in a room where a business school professor moderates a debate to reconcile advice and finalize objectives for the next eight weeks.

Table 1: Summary Statistics of Mentors

	Mean	Median	Standard Deviation	Min	Max
Panel A: Angel Investors (N = 44)					
Former Founder	1.00	1	0.00	1	1
Exited Entrepreneur	0.61	1	0.49	0	1
Mentorship Hours Committed	27.91	26	16.20	4	76
Unique Startups Mentored	4.50	4	3.09	1	18
Panel B: Venture Capitalists (N = 148)					
Former Founder	0.49	0	0.50	0	1
Exited Entrepreneur	0.32	0	0.47	0	1
Mentorship Hours Committed	22.73	16	20.64	4	152
Unique Startups Mentored	4.07	3	3.36	1	25

Notes: This table summarizes the startup experience and mentoring intensity of angels and VCs.

of my sample. So, in Data Appendix appendix A.3 I assess representativeness by comparing my sample to several other samples used by prior studies.

3 Empirical Approach

The statistical analysis follows Stern (2004), who examines scientists' willingness to pay for academic freedom by constructing each worker's bundle of job choices. Similarly, I analyze mentors' willingness to provide experimentation advice by constructing each mentor's bundle of startup choices. Sample data shown in Appendix table B1 demonstrates this structure in panel data.

The estimation strategy models the provision of mentor advice as a function of whether the startup's top priority objective is experimentation and whether the mentor is an angel or a VC:

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

The dependent variable $Advice_{ijt}$ is an indicator that equals 1 if mentor i chooses to advise startup j in 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 changes

Table 2: Summary Statistics of Startups

$N = 253$	Mean	Median	Standard Deviation	Min	Max
Panel A: Venture Characteristics					
Firm Size	4.13	3	5.52	0	50
Founding Team Size	2.55	2	1.22	1	8
Has Industry Advisor	0.64	1	0.48	0	1
Has Prototype	0.23	0	0.42	0	1
Patent IP Strategy	0.71	1	0.46	0	1
Panel B: Founder Characteristics					
Num. PhD Founders	1.04	1	1.22	0	5
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
Panel C: Financial Characteristics					
Capital ($000s)	514.04	67	1,523.20	0	20,000
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

Notes: This table describes pre-program characteristics of startups in Panels A and B. Pre- and post-program financial performance is in Panel C. Pre-program features are from startup applications, first session dossiers, and Internet search. Post-program funding data are sourced from LinkedIn, Pitchbook, Crunchbase, founders, and mentors.

in the same mentors' provision of advice to the same startups over time. Because mentors are active investors, changes in the growth potential of startups may confound mentoring decisions. While I directly test the role of financial incentives in mentoring decisions, I also add a vector of time-varying indicators $\boldsymbol{x}_{jt}$ to alleviate this concern in the main estimates. 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 investment opportunity.

The equation is estimated using fixed effects logit models with standard errors clustered by startup. The main coefficient of interest β_1 is interpreted as the odds ratio of receiving experimentation advice from angels compared to receiving it from VCs. A major empirical challenge of my estimation strategy is to measure the variable $Experiment_{jt}$–that is, to accurately classify several thousand uniquely worded objectives at a conceptual level. In the next section, I describe how I overcome this challenge by developing a novel classification of startup activities.

3.1 A Novel Typology of Early-Stage Startup Activities

fig. 3 displays the classification system I develop and use to categorize startup objectives. To my knowledge, this is the first typology that leverages large-scale data, 4,542 business objectives to be precise, to link granular startup activities to the theoretical foundations of strategy. Akin to the case study method of Eisenhardt (1989), I develop this model using insights from observing and cataloguing early firm development in several hundred startups during a seven-year research fellowship at SEP. The present work builds on and extends few but notable prior attempts by Carter *et al.* (1996), Reynolds (2000), and Bennett & Chatterji (2019).[6] In table B2, I present a detailed comparison of the differences and similarities between my classification and each of these existing models.

To develop this classification, I first draw on bodies of knowledge in strategy, economics, and finance to define both what is and what is not experimentation. Then, I use a systematic and replicable labelling procedure to classify objectives. I now describe these two steps in order.

3.1.1 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).[7] 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, 2013), or a method of inference (Koning *et al.*, 2022).

As noted in the introduction, the classical competitive strategy also highlights learning through analysis, whereby entrepreneurs generate options via search and choose via optimization (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

[6] Carter *et al.* (1996) survey nascent entrepreneurs on 14 precursor activities, finding that some (e.g., prototyping) differ substantially between persisting and abandoning entrepreneurship. Another large-scale survey that spurred several studies divides activities into pre- and post-registration (Reynolds, 2000). Bennett & Chatterji (2019) survey entrepreneurs on 21 pre-entry activities, finding that nascent entrepreneurs are more likely to make significant commitments early-on than to engage in learning.

[7] Respective examples are “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.”

Figure 3: Typology of Early-Stage Startup Activities

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 examples for each of the four conceptual category of startup activity.

organization (Shane & Delmar, 2004; Delmar & Shane, 2003).[8]

Experimentation differs from analysis in that it is more costly but also yields higher-fidelity signals (Aghion *et al.*, 1991; Gans *et al.*, 2021). 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.[9]

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 fig. 4 displays the distribution of each category among startup objectives. Interestingly, the median occurrence of all categories is roughly equal indicating the balanced priority of each category among startups' business objectives.

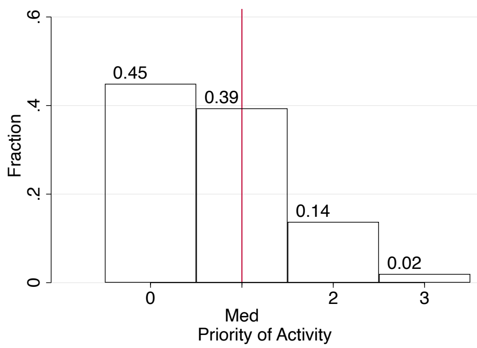
3.1.2 Labelling Procedure

Directly labelling thousands of objectives at a conceptual level is prone to bias and cognitive error. So, I adopt a multi-step approach to first reduce the dimensionality of objectives to a small set of

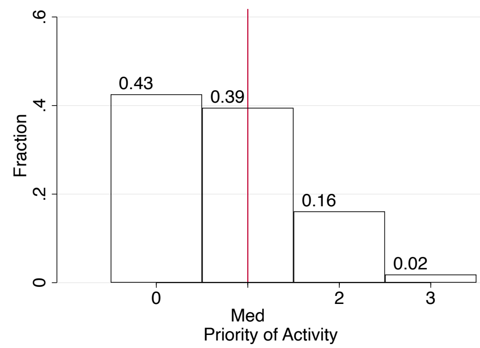
[8] Respective example are "identify ten types of crops with the biggest market in North America," "identify specific beachhead markets," and "prepare capital forecast for next raise."

[9] Companies such as ProductBoard utilize this standardization to offer business planning and product roadmap development services to startups.

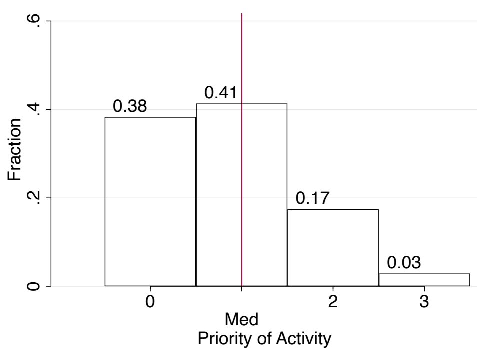
Figure 4: Distribution of the Conceptual Categories in Startup Objectives



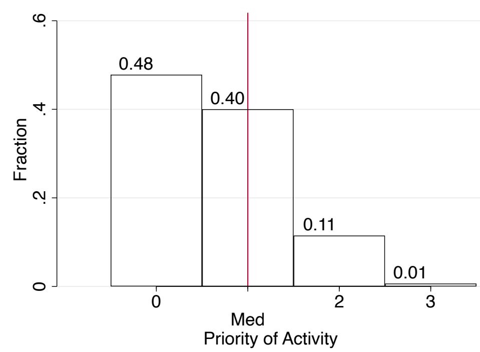
(a) Analysis



(b) Experimentation



(c) Implementation



(d) Resource Acquisition

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

distinct business functions, then map these functions to the categories described earlier.

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 sensitivity of clustering. So, I review each group from the smallest (some containing only one objective) to largest, and merge them when there is significant overlap in terms of the core business function of the objective (e.g., merge the group for marketing videos with the group on creating marketing collateral). Repeating this exercise two more times, I reach a set of distinct business "activities" that cannot be further reduced. For validation, three undergraduate students assign a unique label from this final list of activities to the raw text of the objectives, which match mine 95% of the time. Finally, based on the definitions developed earlier, I map each activity to a conceptual category as illustrated in fig. 3 by connecting lines.

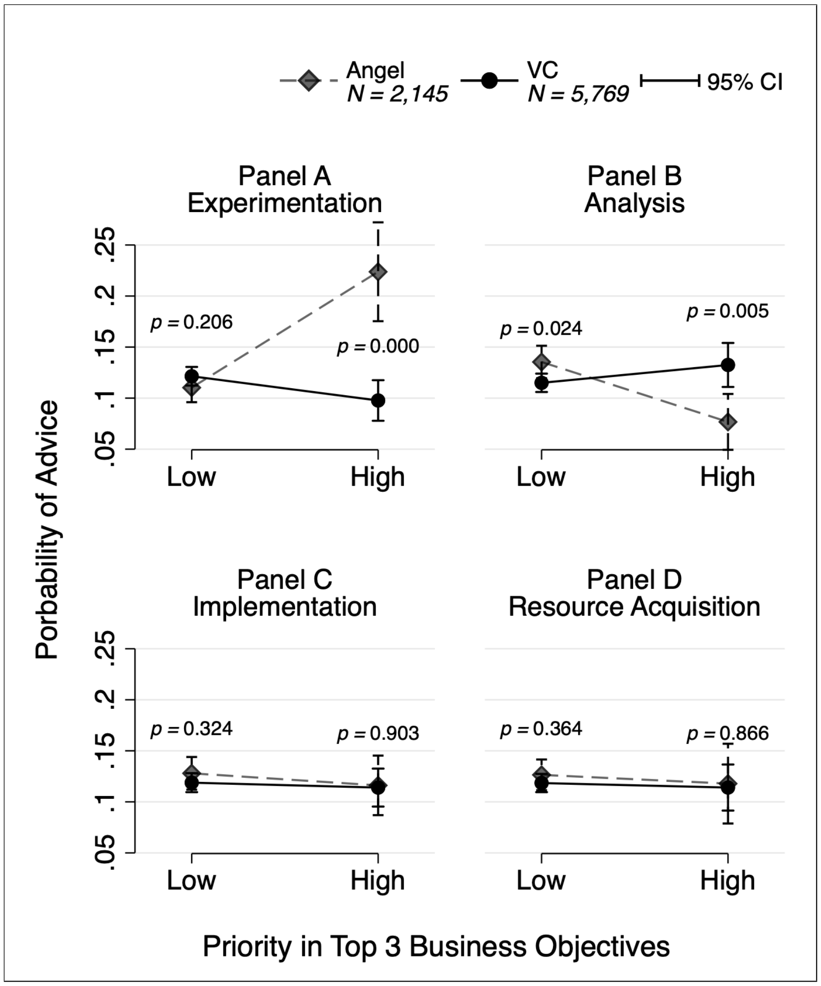
In Appendix table B3, I catalogue examples and exclusions for each business activity. In Appendix table B4, I compare the objectives before and after founders received feedback from mentors. One interesting pattern is that, compared to mentors, entrepreneurs under-prioritize learning.

4 Main Results

fig. 5 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. Specifically, Panel A shows that when running experiments is not the main priority of the firm, angels and VCs are roughly equally likely to provide advice (p-value = 0.206). However, when running experiments is the top priority, the probability of angels providing advice doubles from 0.11 to 0.22, which is significantly larger than this probability for VCs. Alternatively, Appendix table B5 shows that the priority of experimentation among angel-mentored startups is 26% higher than among VC-mentored startups.

Moving on to the Panel B of fig. 5, I find that VCs are instead more likely than angels to provide advice when analysis is the main priority of the business. Furthermore, Panels C and D show that no such pattern exists in the mentoring decisions of angels and VCs for non-learning activities–implementation and resource acquisition. While illustrative, these univariate tests do not account for differences in the quality of startups or the unobserved differences between mentors.

Figure 5: The Probability of Advice by Angels versus VCs
by the Type of Business Objectives Supported



Notes: This graph shows the probability of angels and of VCs providing advice to startups under different conditions. High Experiment (Low Experiment) means that two or more (one or zero) of the firm's top-three objectives are to perform experiments. High (Low) analysis, implementation, and resources acquisition are defined analogously.

Table 4: The Probability of Angels vs. VCs to Provide Experimentation Advice: FE Logits

DV = Advice	(4-1)	(4-2)	(4-3)
Angel	0.078		
	(0.107)		
Experiment	–0.061	–0.419***	
	(0.078)	(0.106)	
Experiment × Angel		1.169***	
		(0.185)	
Analysis			0.177*
			(0.091)
Analysis × Angel			–0.816***
			(0.256)
Revenue Positive		–0.091	–0.114
		(0.130)	(0.130)
AbvMed Funding		0.089	0.113
		(0.100)	(0.102)
Open Round		0.119*	0.122*
		(0.068)	(0.068)
Startup FE	Yes	Yes	Yes
Mentor FE		Yes	Yes
ℓ	-2,466.0	-2,383.0	-2,391.7
N	7,914	7,914	7,914

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

The remaining multivariate analyses tackle these issues.

table 4 shows the results from estimating eq. (1) with fixed effects logits. In Model 4-1, the coefficient for $Angel_i$ implies that angels and VCs are indistinguishable in terms of the amount of time they commit to mentoring startups–they are roughly equally likely to provide advice. The small and insignificant coefficient for $Experiment_{jt}$ also suggest that being in an experimentation phase does not significantly correlate with the probability of receiving advice.

Model 4-2 adds the main interaction term $Experiment_{jt} \times Angel_i$ as well as mentor fixed effects, which restricts the analysis to mentors who make at least two mentoring decisions. The coefficient of interest is estimated 1.169 at the 1% significance level, meaning that angels are roughly 3 times more likely than VCs to provide experimentation advice. Appendix table B6 further shows that these results are robust to a linear probability specification as well as to alternative measures of the priority of experimentation.

Moving on to Model 4-3, I find that VCs are instead more likely than are angels to provide advice on analysis. One explanation is that VCs have superior access to market intelligence and experience in planning. As professional investors, VCs are known to develop specialized industry knowledge and connections (Sahlman, 1990; Norton & Tenenbaum, 1993; Gupta & Sapienza, 1992), keep abreast of the latest market developments (Metrick & Yasuda, 2010), and practice financial and strategic planning as their core responsibility (Kaplan & Strömberg, 2004; Gorman & Sahlman, 1989).

4.1 Quality of Advice

This section presents evidence that, in addition to quantity, the quality of angels' advice on experimentation is higher than that of VCs. This evidence is based on a valuable feature of the setting that allows me to observe accurate information on whether founding teams achieve the prioritized objectives for which they received advice. As previously noted, this information is updated before each session and reported on dossiers shown in fig. 1.[10]

It is reasonable to assume that a startup would be more successful in achieving its objectives when the mentoring support it receives is more effective, especially in a setting that is explicitly designed for mentors to support founders business objectives. Thus, I use completion status of objectives as a proxy for the quality of experimentation advice when the advice is provided by an angel versus by a VC. To facilitate interpretation, I use a linear probability model, but results are more significant with fixed effects logits.

Results are shown in table 5. For brevity, I focus on the preferred Model 5-2, which shows that conditional on receiving advice, startups are 6.6 percentage points or 10% more likely to successfully run an experiment when mentored by an angel than by VCs. Results are smaller but similar in significance when the dependent variable is the fraction of experiments completed. Using both startup and mentor fixed effects means that I compare the same startup's performance and advice from the same mentor over different periods. Model 5-3 shows similar results even after adding session fixed effects, which allows to compare experiments initiated at the same point in founders' tenure in the program.

[10] SEP staff are entitled to ask for supporting evidence of completion from founders before approving and releasing dossiers to mentors. Mentors who advise startups are also aware of the outcomes. Lastly, SEP requires objectives to be formulated such that they are *measurable* and *feasible* to achieve within 8 weeks. These valuable properties of the setting make the completion status of objectives quite precise, and largely minimize variation in the quality of objective design.

Table 5: Quality of Experimentation Advice: OLS
Sample of High-Experimentation Priority Observations

DV = Experiment Completed	(5-1)	(5-2)	(5-3)
Advice	-0.042^{***}	-0.037^{***}	-0.025^{**}
	(0.012)	(0.013)	(0.010)
Angel	-0.005		
	(0.005)		
Advice × Angel	0.078^{***}	0.066^{**}	0.058^{**}
	(0.030)	(0.031)	(0.027)
Startup FE	Yes	Yes	Yes
Mentor FE		Yes	Yes
Session FE			Yes
N	4,395	4,395	4,395

Notes: This table shows the completion rate of startups' business objectives as a function of the type of mentor who provided advice. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

To the extent that advice drives timely completion of experiments, these results extend Camuffo *et al.* (2020). While Camuffo and colleagues show that mentoring unlocks the benefits of experimentation, my results suggest that *who* provides the advice is also important. This further speaks to potential complementarities between angel and VC value-added, though more research is needed to assess long-term performance implications for firm growth (see Hellmann *et al.*, 2021, for a recent study).

5 Mechanism: Learning-by-Doing

This section shows that the main finding that angels provide more experimentation advice than VCs is driven by angels who have experience in founding and scaling startups. Furthermore, this experience channel is only salient when founders lack meaningful startup experience, and only for experimentation, not for other types of activity. These results are consistent with the hypothesis that angels have a skill advantage in experimentation because, as predominantly successful former founders, they have more operating experience than do VCs.

For the empirical assessment, I first collect data on whether each founder and mentor is a former founder. These data are from Pitchbook, Crunchbase, LinkedIn, and specifically for founders, also from their applications to SEP. For mentors, however, this measure poses an empirical challenge. From mentors' summary statistics in table 1, all angels in my sample are former founders, which is

Table 6: Experimentation Advice and the Operating Experience of Mentors: FE Logits Split-Sample Regressions

DV = Advice	Angels		VCs	
	(6-1) Exited	(6-2) No Exit	(6-3) Exited	(6-4) No Exit
Experiment	0.960***	0.390	–0.364	–0.410**
	(0.329)	(0.293)	(0.222)	(0.167)
Startup FE	Yes	Yes	Yes	Yes
Mentor FE	Yes	Yes	Yes	Yes
ℓ	-197.0	-142.7	-479.4	-934.8
N	1,187	958	2,071	3,698

Notes: This table shows the likelihood of providing advice on experiments compared to other types of activity in subsamples of angels and VCs split by exit history. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

consistent with prior studies (Ibrahim, 2008; Linde *et al.*, 2000). This invariability makes founding history useless for examining the role of experience in angel advice. Even if there was variation, founding history alone is a noisy measure of the type and 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 successfully grows their firm to a mature stage. So, consistent with prior studies (e.g., Gompers *et al.*, 2010), I collect data on whether ex-founder mentors successfully exited via acquisition or IPO. Exit sets a clear market-based threshold for substantive experience in founding and growing a scalable firm.

table 6 presents the results. Models 6-1 and 6-2 show the main results within subsamples of mentoring decisions made by exited and non-exited angels. These results show that only exited angels are significantly more likely to provide advice on experiments than other activities. Similarly for VCs, split-sample results in Models 6-3 and 6-4 show that VCs' lack of interest in mentoring experiments is mainly driven by non-exited VCs.

If experience endows experimentation skills, and mentors' decisions are driven by the support needs of the founding teams, then inexperienced founding teams who have a larger gap in their entrepreneurial skills should receive more support on their experimentation objectives. In my data, 41% of founding teams have an ex-founder, and 42% have a founder who has worked for a startup. I leverage this variation in teams' past startup experience to estimate a model of the form

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

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

fig. 6 visualizes the results. The left two 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 "No" estimates show whether experienced mentors provide more experimentation advice than inexperienced mentors to teams without any startup experience (β_2), and the "Yes" shows this for teams with startup background ($\beta_1 + \beta_2$).

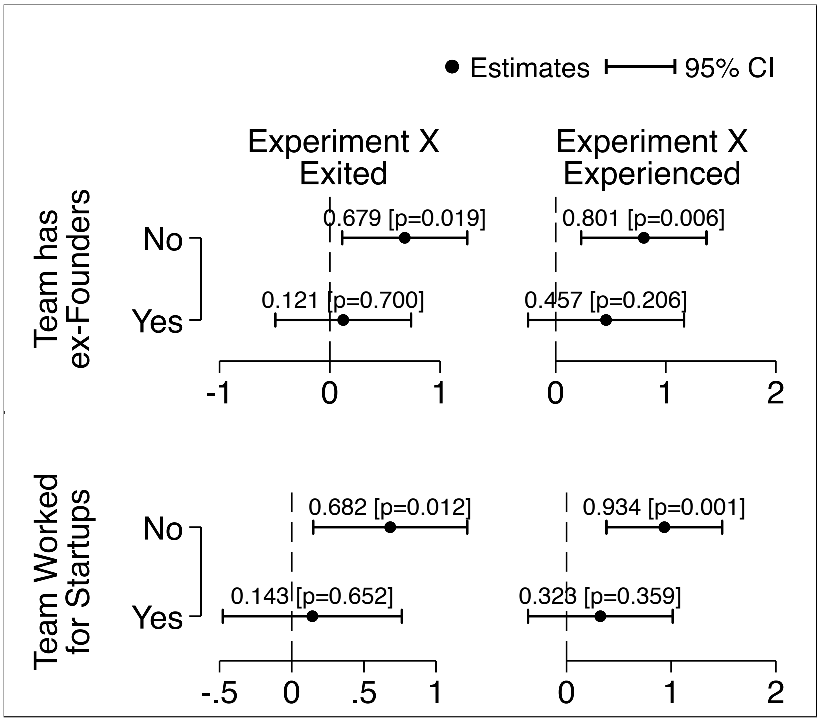
Across all measures of experience, experienced mentors are only more likely to provide experimentation advice than other types of advice to the teams who lack practical startup background. Appendix fig. B1 further shows that this pattern of findings only holds for experimentation and so is not driven by broader substitution effects in mentor-mentee stocks of experience.

These findings also support the internal validity of my study by reinforcing mentoring decisions are based on founder skill gaps. However, this is not enough to rule out alternative mechanisms consistent with the main findings. In the next section, I tackle the most important of these explanations, financial incentives. In Figures and Tables Appendix, I also examine and rule out other explanations due to selection issues based on information preferences (table B7), startup stage (table B8), and sorting (table B9).

5.1 Financial Incentives of Mentors

By mentoring, investors learn quality signals that can preempt information asymmetry with investment targets, which mitigates a foremost challenge of startup financing (Gompers & Lerner, 2001).

Figure 6: Heterogeneity of Experimentation Advice by Founder and Mentor Experience: FE Logits



Notes: This figure shows point estimates, 95% CIs, and p-values for heterogeneity in experimentation advice by founder and mentor experience from four different regressions, corresponding to the two different measures of experience used for founders and mentors.

This can explain my results if the intensity of financial incentives differs systematically between angels and VCs. For example, VCs may have stronger incentives to prioritize deal flow than angels do as their compensation is tightly linked to committing their capital within a limited time horizon (Barrot, 2017). Therefore, they may be reluctant to mentor startups that do not need capital, which can drive my results if such startups also need less experimentation advice.

To investigate, I test the sensitivity of advice to the intensity of deal flow incentives measured by whether or not the startup has had an open funding round each time investors were making mentoring decisions. Of course, mentors can anticipate future capital needs. So, I also test sensitivity to the length of time (runway) remaining before the firm runs out of cash and needs to raise.

table 7 Model 7-1 shows that in the full sample even a sharp increase in deal flow incentives does not correlate with the likelihood of advice ($0.139 * [OpenRound_{jt}] - 0.106 * [OpenRound_{jt} \times Angel_i] = 0.034$, p-value = 0.813). Split-sample results of Models 7-2 and 7-3 show that the

Table 7: Sensitivity of Experimentation Advice to Deal Flow Incentives: FE Logits
Full and split-Sample Regressions

DV = Advice	Current Funding			Expected Funding	
	(7-1) Full Sample	(7-2) No Open Round	(7-3) Open Round	(7-4) BlwMed Runway	(7-5) AbvMed Runway
Experiment	–0.408***	–0.355**	–0.371	–0.346	–0.472*
	(0.107)	(0.141)	(0.238)	(0.241)	(0.287)
Experiment × Angel	1.145***	1.008***	1.062***	1.161***	1.143***
	(0.189)	(0.261)	(0.338)	(0.318)	(0.348)
Open Round	0.139				
	(0.091)				
Open Round × Angel	–0.106				
	(0.188)				
Startup FE	Yes	Yes	Yes	Yes	Yes
Mentor FE	Yes	Yes	Yes	Yes	Yes
ℓ	-2,383.0	-1,080.8	-1,085.7	-1,047.6	-1,120.5
N	7,914	3,899	4,015	3,863	4,051

Notes: This table shows the main results under different funding conditions for startups. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

main estimate for $Experiment_{jt} \times Angel_i$ remains quite stable whether or not startups are actively raising capital. Lastly, the similarity of the estimated coefficients for $Experiment_{jt} \times Angel_i$ across Models 7-4 and 7-5 illustrate stability of the experimentation effect also to whether or not the startup is *expected* to raise capital in the near future.

The reader might be surprised by these results: how can competing investors *not* be inclined to utilize mentoring in order to make better financing decisions? One explanation is that opportunistic behavior in a mentoring setting does not lead to better outcomes, or reduce information asymmetry for that matter. In Data Appendix A.4, I further discuss why strategic behavior in a mentoring setting such as the one used herein is generally unlikely.

But a second and more plausible explanation is due to a unique feature of SEP. This feature is the presence of a process whereby at each session mentors can explicitly express their interest in funding startups, which is distinct from the process for gathering mentoring decisions. Put differently, mentors need not commit considerable amount of time to mentoring founders just to learn about and invest in them–they can do so using an alternative voting mechanism.

6 Conclusion and 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 and startups are more likely to succeed in experimentation given angels' advice. I also present evidence that angels have a skill advantage in experimentation because they have learned how to run effective experiments by doing–as they have in 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 both current and expected capital requirements of startups change sharply. The detail in data also allows me to test and rule out other alternative explanations due to information preferences, stage preferences, and sorting.

This study offers new insights for our understanding of investor strategy, especially in selecting and supporting their portfolio firms. Venture capital spurs economic growth by growing science projects into successful businesses, but also by picking winning ideas in the first place (Baum & Silverman, 2004). For the selection process, Shepherd (1999) shows that funders prioritize the firm's capability to learn and grow, while Aggarwal *et al.* (2015) show that this evaluation itself depends on the ability of the investors to ascertain firm quality. I extend this latter insight by suggesting a broader fit between investment strategy and investor capability whereby investors anticipate their own value-added potential in assessing the growth potential of the risky ideas. 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 as to why angels obtain weaker control rights than VCs (see Goldfarb *et al.*, 2013), despite investing in presumably riskier deals (Dessein, 2005). While Kaplan & Strömberg (2004) find that value-added potential is not related to control rights, my results suggest that certain types of value-added such as advice may mitigate moral hazard problems that are traditionally predicted to increase control provisions (Holmstrom, 1979). Put differently, angels may seek fewer control rights because they anticipate more influence on experiments that shape the direction of the firm's strategic decisions.

In terms of future research, this paper offers a new direction for scholars who aim to understand the competitive dynamics of the venture capital industry and its strategic implications for entrepreneurs. Studies that explore the complementarities between angels and VCs, and investor switching (Goldfarb *et al.*, 2013; Hellmann *et al.*, 2021) may find new explanatory power in investors' mentoring ability. Such research can also guide models of the equilibrium dynamics between angels and VCs to incorporate non-financial services in their theories (e.g. Hellmann & Thiele, 2015). Future research can also build on this study to further the insights from Hsu (2004) who shows that entrepreneurs accept lower valuations to associate with more reputable investors. Using the framework I offer for measuring the type and quality of advice, scholars can examine the efficiency of this market for affiliation.

This study has two main limitations. First, it is difficult to accurately compare the representativeness of my startup sample to the population of high-technology startups. In the Data Appendix, I mitigate this concern by extensively comparing the characteristics of my sample to several other samples and settings of U.S.-based high-technology startups. Overall, I find high overlap in terms of team, technology, and financial performance characteristics. Second, establishing a causal relationship between mentor type and business advice requires randomly varying startups' business objectives. This is impossible. So instead, I attempt to address key endogeneity concerns by holding both investor and startup characteristics constant, while also identifying and ruling out several alternative explanations.

References

Aggarwal, Rohit, Kryscynski, David, & Singh, Harpreet. 2015. Evaluating Venture Technical Competence in Venture Capitalist Investment Decisions. *Management science*, **61**(11), 2685–2706. Place: Linthicum Publisher: INFORMS.

Aghion, Philippe, Bolton, Patrick, Harris, Christopher, & Jullien, Bruno. 1991. Optimal learning by experimentation. *The review of economic studies*, **58**(4), 621–654.

Agrawal, Ajay, Gans, Joshua S, & Stern, Scott. 2021. Enabling entrepreneurial choice. *Management Science*.

Amore, Mario Daniele, Conti, Annamaria, & Pelucco, Valerio. 2022. Micro VC. *DP17258*.

Ariely, Dan, Bracha, Anat, & Meier, Stephan. 2009. Doing good or doing well? Image motivation and monetary incentives in behaving prosocially. *American economic review*, **99**(1), 544–55.

Barrot, Jean-Noël. 2017. Investor horizon and the life cycle of innovative firms: Evidence from venture capital. *Management Science*, **63**(9), 3021–3043.

Baum, Joel AC, & Silverman, Brian S. 2004. Picking winners or building them? Alliance, intellectual, and human capital as selection criteria in venture financing and performance of biotechnology startups. *Journal of business venturing*, **19**(3), 411–436.

Bennett, Victor M, & Chatterji, Aaron K. 2019. The entrepreneurial process: Evidence from a nationally representative survey. *Strategic Management Journal*.

Bergemann, Dirk, & Hege, Ulrich. 2005. The financing of innovation: Learning and stopping. *RAND Journal of Economics*, 719–752.

Bernstein, Shai, Giroud, Xavier, & Towsend, Richard R. 2016. The Impact of Venture Capital Monitoring. *The Journal of finance (New York)*, **71**(4), 1591–1622. Place: Cambridge Publisher: Blackwell Publishing Ltd.

Bernstein, Shai, Korteweg, Arthur, & Laws, Kevin. 2017. Attracting early-stage investors: Evidence from a randomized field experiment. *The Journal of Finance*, **72**(2), 509–538.

Blank, Steve. 2013. *The four steps to the epiphany*. K & S Ranch.

Camuffo, Arnaldo, Cordova, Alessandro, Gambardella, Alfonso, & Spina, Chiara. 2020. A scientific approach to entrepreneurial decision making: Evidence from a randomized control trial. *Management Science*, **66**(2), 564–586.

Carter, Nancy, Gartner, William, & Reynolds, Paul. 1996. Exploring Start-Up Event Sequences. *Journal of Business Venturing*, **11**(02), 151–166.

Casamatta, Catherine. 2003. Financing and advising: optimal financial contracts with venture capitalists. *The journal of finance*, **58**(5), 2059–2085.

Chatterji, Aaron, Delecourt, Solène, Hasan, Sharique, & Koning, Rembrand. 2019. When does advice impact startup performance? *Strategic Management Journal*, **40**(3), 331–356.

Chemmanur, Thomas J, & Chen, Zhaohui. 2014. Venture capitalists versus angels: The dynamics of private firm financing contracts. *The Review of Corporate Finance Studies*, **3**(1-2), 39–86.

Cohen, Susan, & Hochberg, Yael V. 2014. Accelerating startups: The seed accelerator phenomenon. *Available at SSRN 2418000*.

Cohen, Susan, Fehder, Daniel C, Hochberg, Yael V, & Murray, Fiona. 2019a. The design of startup accelerators. *Research Policy*, **48**(7), 1781–1797.

Cohen, Susan L, Bingham, Christopher B, & Hallen, Benjamin L. 2019b. The role of accelerator designs in mitigating bounded rationality in new ventures. *Administrative Science Quarterly*, **64**(4), 810–854.

Cumming, Douglas J., & MacIntosh, Jeffrey G. 2006. Crowding out private equity: Canadian evidence. *Journal of Business Venturing*, **21**(5), 569–609.

Da Rin, Marco, Hellmann, Thomas, & Puri, Manju. 2013. A survey of venture capital research. *Pages 573–648 of: Handbook of the Economics of Finance*, vol. 2. Elsevier.

Delmar, Frederic, & Shane, Scott. 2003. Does business planning facilitate the development of new ventures? *Strategic management journal*, **24**(12), 1165–1185.

Dessein, Wouter. 2005. Information and control in ventures and alliances. *The Journal of Finance*, **60**(5), 2513–2549.

Eisenhardt, Kathleen M. 1989. Building theories from case study research. *Academy of management review*, **14**(4), 532–550.

Eisenhardt, Kathleen M, & Schoonhoven, Claudia Bird. 1990. Organizational growth: Linking founding team, strategy, environment, and growth among US semiconductor ventures, 1978-1988. *Administrative science quarterly*, 504–529.

Ewens, Michael, & Rhodes-Kropf, Matthew. 2015. Is a VC Partnership Greater than the Sum of its Partners? *The Journal of Finance*, **70**(3), 1081–1113.

Ewens, Michael, Nanda, Ramana, & Rhodes-Kropf, Matthew. 2018. Cost of experimentation and the evolution of venture capital. *Journal of Financial Economics*, **128**(3), 422–442.

Felin, Teppo, Gambardella, Alfonso, Stern, Scott, & Zenger, Todd. 2019. Lean startup and the business model: Experimentation revisited. *Forthcoming in Long Range Planning (Open Access)*.

Gans, Joshua S. 2018. *A Better Way to Bring Science to Market*.

Gans, Joshua S., Hsu, David H., & Stern, Scott. 2002. When Does Start-Up Innovation Spur the Gale of Creative Destruction? *The RAND Journal of Economics*, **33**(4), 571–586.

Gans, Joshua S, Stern, Scott, & Wu, Jane. 2019. Foundations of entrepreneurial strategy. *Strategic Management Journal*, **40**(5), 736–756.

Gans, Joshua S, Scott, Erin, & Stern, Scott. 2021. *Entrepreneurship: A Strategic Approach*. Norton: New York.

Gneezy, Uri, Meier, Stephan, & Rey-Biel, Pedro. 2011. When and why incentives (don't) work to modify behavior. *Journal of economic perspectives*, **25**(4), 191–210.

Goldfarb, Avi, & Xiao, Mo. 2011. Who thinks about the competition? Managerial ability and strategic entry in US local telephone markets. *American Economic Review*, **101**(7), 3130–61.

Goldfarb, Brent D, Hoberg, Gerard, Kirsch, David, & Triantis, Alexander J. 2013. Are angels different? An analysis of early venture financing. *An Analysis of Early Venture Financing (November 4, 2013). Robert H. Smith School Research Paper No. RHS*, 06–072.

Gompers, Paul, & Lerner, Josh. 1999. An analysis of compensation in the US venture capital partnership. *Journal of Financial Economics*, **51**(1), 3–44.

Gompers, Paul, & Lerner, Josh. 2001. The venture capital revolution. *Journal of economic perspectives*, **15**(2), 145–168.

Gompers, Paul, Kovner, Anna, Lerner, Josh, & Scharfstein, David. 2010. Performance persistence in entrepreneurship. *Journal of financial economics*, **96**(1), 18–32.

Gompers, Paul A, & Mukharlyamov, Vladimir. 2022 (April). *Transferable Skills? Founders as Venture Capitalists*. Working Paper 29907. National Bureau of Economic Research.

Gorman, Michael, & Sahlman, William A. 1989. What do venture capitalists do? *Journal of business venturing*, **4**(4), 231–248.

Gruber, Marc, MacMillan, Ian C, & Thompson, James D. 2008. Look before you leap: Market opportunity identification in emerging technology firms. *Management science*, **54**(9), 1652–1665.

Gupta, Anil K, & Sapienza, Harry J. 1992. Determinants of venture capital firms' preferences regarding the industry diversity and geographic scope of their investments. *Journal of business Venturing*, **7**(5), 347–362.

Hallen, Benjamin L, Cohen, Susan L, & Bingham, Christopher B. 2020. Do Accelerators Work? If So, How? *Organization Science*, **31**(2), 378–414.

Harrison, Richard T, & Mason, Colin M. 2007. Does gender matter? Women business angels and the supply of entrepreneurial finance. *Entrepreneurship Theory and Practice*, **31**(3), 445–472.

Hellmann, Thomas, & Puri, Manju. 2000. The interaction between product market and financing strategy: The role of venture capital. *The review of financial studies*, **13**(4), 959–984.

Hellmann, Thomas, & Puri, Manju. 2002. Venture capital and the professionalization of start-up firms: Empirical evidence. *The journal of finance*, **57**(1), 169–197.

Hellmann, Thomas, & Thiele, Veikko. 2015. Friends or foes? The interrelationship between angel and venture capital markets. *Journal of Financial Economics*, **115**(3), 639–653.

Hellmann, Thomas, Schure, Paul, & Vo, Dan H. 2021. Angels and venture capitalists: Substitutes or complements? *Journal of Financial Economics*, **141**(2), 454–478.

Hochberg, Yael V. 2016. Accelerating entrepreneurs and ecosystems: The seed accelerator model. *Innovation Policy and the Economy*, **16**(1), 25–51.

Hochberg, Yael V, Ljungqvist, Alexander, & Lu, Yang. 2007. Whom you know matters: Venture capital networks and investment performance. *The Journal of Finance*, **62**(1), 251–301.

Holmstrom, Bengt. 1979. Moral Hazard and Observability. *The Bell Journal of Economics*, 74–91.

Horowitz, Ben. 2010 (Mar.). *Angels vs. Venture Capitalists*.

Howell, Sabrina T. 2020. Reducing information frictions in venture capital: The role of new venture competitions. *Journal of Financial Economics*, **136**(3), 676–694.

Hsu, David H. 2004. What do entrepreneurs pay for venture capital affiliation? *The Journal of Finance*, **59**(4), 1805–1844.

Hsu, David H. 2007. Experienced entrepreneurial founders, organizational capital, and venture capital funding. *Research policy*, **36**(5), 722–741.

Hsu, David H, Roberts, Edward B, & Eesley, Charles E. 2007. Entrepreneurs from technology-based universities: Evidence from MIT. *Research Policy*, **36**(5), 768–788.

Ibrahim, Darian M. 2008. The (not so) puzzling behavior of angel investors. *Vand. L. Rev.*, **61**, 1405.

Jensen, Richard, & Thursby, Marie. 2001. Proofs and prototypes for sale: The licensing of university inventions. *American Economic Review*, **91**(1), 240–259.

Kaplan, Steven N, & Strömberg, Per ER. 2004. Characteristics, contracts, and actions: Evidence from venture capitalist analyses. *The Journal of Finance*, **59**(5), 2177–2210.

Kerr, William R, Lerner, Josh, & Schoar, Antoinette. 2014a. The consequences of entrepreneurial finance: Evidence from angel financings. *The Review of Financial Studies*, **27**(1), 20–55.

Kerr, William R, Nanda, Ramana, & Rhodes-Kropf, Matthew. 2014b. Entrepreneurship as experimentation. *Journal of Economic Perspectives*, **28**(3), 25–48.

Koning, Rembrand, Hasan, Sharique, & Chatterji, Aaron. 2022. Experimentation and Start-up Performance: Evidence from A/B Testing. *Management Science*.

Lauff, C. A. 2018. What is a Prototype? What are the Roles of Prototypes in Companies? *Journal of Mechanical Design*, **140**(6).

Lerner, Joshua. 2009. *Boulevard of broken dreams why public efforts to boost entrepreneurship and venture capital have failed and what to do about it*. Course book edn. The Kauffman Foundation series on innovation and entrepreneurship. Princeton: Princeton University Press.

Leshchinskii, Dima. 2003. *Indulgent angels or stingy venture capitalists?: the entrepreneurs' choice*. Groupe HEC.

Levinthal, Daniel A. 2017. Mendel in the C-Suite: Design and the Evolution of Strategies. *Strategy Science*, **2**(4), 282–287.

Liang, James, Wang, Hui, & Lazear, Edward P. 2018. Demographics and entrepreneurship. *Journal of Political Economy*, **126**(S1), S140–S196.

Linde, Lucinda, Prasad, Alok, Morse, KP, Utterback, M, Stevenson, H, & Roberts, M. 2000. Venture support systems project: angel investors. *Unpublished manuscript, MIT Entrepreneurship Center*.

Manso, Gustavo. 2016. Experimentation and the Returns to Entrepreneurship. *The Review of Financial Studies*, **29**(9), 2319–2340.

March, James G. 1991. Exploration and exploitation in organizational learning. *Organization science*, **2**(1), 71–87.

Mason, Colin M, & Harrison, Richard T. 2002. Barriers to investment in the informal venture capital sector. *Entrepreneurship & Regional Development*, **14**(3), 271–287.

McGrath, Rita Gunther, & MacMillan, Ian C. 1995. *Discovery driven planning*. Wharton School, Snider Entrepreneurial Center Philadelphia.

Metrick, Andrew, & Yasuda, Ayako. 2010. The economics of private equity funds. *The Review of Financial Studies*, **23**(6), 2303–2341.

Miller, Paul, & Bound, Kirsten. 2011. The startup factories. *NESTA. http://www. nesta. org. uk/library/documents/StartupFactories. pdf*.

Nanda, Ramana, & Rhodes-Kropf, Matthew. 2017. Financing risk and innovation. *Management Science*, **63**(4), 901–918.

Nelson, Richard. 1997. How new is new growth theory? *Challenge*, **40**(5), 29–58.

New York Times. 2015. Angel Investors Lend Expertise as Well as Cash. Mar.

Norton, Edgar, & Tenenbaum, Bernard H. 1993. Specialization versus diversification as a venture capital investment strategy. *Journal of Business venturing*, **8**(5), 431–442.

OECD. 2011. *Financing High-Growth Firms: The Role of Angel Investors*. Paris: OECD.

Porter, Michael E. 1980. *Competitive strategy: Techniques for analyzing industries and competitors*. Simon and Schuster.

Reynolds, Paul. 2000. National Panel Study of U.S. Business Startups: Background and Methodology. *Advances in Entrepreneurship, Firm Emergence and Growth*, **4**, 153–227.

Ries, Eric. 2011. *The lean startup: How today's entrepreneurs use continuous innovation to create radically successful businesses*. Crown Books.

Ruef, Martin, Aldrich, Howard E, & Carter, Nancy M. 2003. The structure of founding teams: Homophily, strong ties, and isolation among US entrepreneurs. *American sociological review*, **68**(2), 195–222.

Sahlman, William A. 1990. The structure and governance of venture-capital organizations. *Journal of financial economics*, **27**(2), 473–521.

Schwienbacher, A. 2009. Financing Commitments and Investors Incentives in Entrepreneurial Firms. London School of Economics and Political Science. *Working paper, No. 071/2009*.

Scott, Erin L, Shu, Pian, & Lubynsky, Roman M. 2019. Entrepreneurial uncertainty and expert evaluation: An empirical analysis. *Management Science*.

SEC. 2022. *What are the differences in friends and family, angel investors, and venture capital funds?*

Shane, Scott. 2000. Prior knowledge and the discovery of entrepreneurial opportunities. *Organization science*, **11**(4), 448–469.

Shane, Scott, & Delmar, Frederic. 2004. Planning for the market: business planning before marketing and the continuation of organizing efforts. *Journal of Business Venturing*, **19**(6), 767–785.

Shepherd, Dean A. 1999. Venture Capitalists' Assessment of New Venture Survival. *Management science*, **45**(5), 621–632. Place: Linthicum, MD Publisher: INFORMS.

Sohl, Jeffrey E. 2003. The US angel and venture capital market: Recent trends and developments. *The Journal of Private Equity*, **6**(2), 7–17.

Sørensen, Morten. 2007. How smart is smart money? A two-sided matching model of venture capital. *The Journal of Finance*, **62**(6), 2725–2762.

Sorenson, Olav, & Stuart, Toby E. 2001. Syndication networks and the spatial distribution of venture capital investments. *American journal of sociology*, **106**(6), 1546–1588.

Stern, Scott. 2004. Do scientists pay to be scientists? *Management science*, **50**(6), 835–853.

Wadhwa, Vivek, Freeman, Richard, & Rissing, Ben. 2010. Education and Tech Entrepreneurship. *Innovations: Technology, Governance, Globalization*, **5**(2), 141–153.

Appendix A Data Appendix

A.1 Sample Construction and Attrition

Startups: 1,925 startups applied to the 2018-19 cohort of SEP, from which 389 were admitted to the program. Of this set, 95 were dropped from the program after their first session because they received no mentorship interest at all. Six more startups were dropped because the business objectives of the startup could not be found. One was dropped because it participated in only two sessions where there were only VC mentors. Finally, 34 startups were dropped because only mentors who were neither a VC or an angel voted for them (e.g., exited entrepreneurs who are not active investors). The 253 startups in my sample are the cohort remaining following this process.

Mentors: From the 262 mentors who committed their time at least once, 55 were dropped because they were neither an angel nor a VC. 14 were dropped because they were both an angel and a VC (made both personal and partner investments), and 1 VC was dropped because they only participated in VC-only mentoring sessions. This process yielded the 192 mentors that exist in my analysis.

A.2 Variable Definitions

Mentor type: A mentor is an angel if, from January 2018 to December 2019 (8 months before and 8 months after the study period), they made a personal investment. A mentor is a VC if they made a partner investment during the same period. Mentors that are both or neither type are dropped from the sample (see the next section). Data are from Pitchbook, Crunchbase, and LinkedIn, complemented by first-hand information from SEP staff, mentors, and founders.

Operating experience: Two variables that measure operating experience are whether the mentor has founded a company at all, and whether the mentor has exited their startup via an IPO or an acquisition. These data are from Pitchbook, Crunchbase, and LinkedIn, complemented by first-hand information from SEP staff, mentors, and founders.

A.3 Startup Sample Representativeness

This section compares several characteristics of the startups in my sample to the characteristics of multiple other samples used in prior empirical studies.

The number of founders and employees are similar to the 2.6 founders and 3.4 employees found in the sample of seed-stage startups in AngelList as reported in Bernstein *et al.* (2017). Also, my sample's average size of founding teams is similar to the 2.9 of the MIT E-Lab startups reported in Hsu (2007). In terms of the development stage, 23% of startups in my sample have a prototype at the time of applying to the program, which is close to the 29% of university-based projects in the U.S., as reported in Jensen & Thursby (2001).

The high technology nature of the companies is similar to SBIR and VC-funded startups (Gans *et al.*, 2002). Furthermore, startups have at least one PhD founder, two times higher than startups in the MIT E-Lab (Hsu, 2007) and startups in the MIT Venture Mentoring Services (Scott *et al.*, 2019), and four times higher than startups in new venture competitions reported in Howell (2020).

The average founder age in my sample is consistent with other studies (Wadhwa *et al.*, 2010; Hsu *et al.*, 2007). However, it is lower than the 40 years among the U.S.-based startups financed between 2002 and 2010, as reported in Ewens *et al.* (2018) and in the 2010 Global Entrepreneurship Monitor survey (57 countries), as reported in Liang *et al.* (2018). In terms of experience, 41% of entrepreneurs in my sample claim to have prior founding experience, which is slightly less than the U.S.-based startups in Ewens *et al.* (2018). Lastly, 26% of my startups have at least one female founder, which reflects the documented under-representation of women in tech entrepreneurship (Ruef *et al.*, 2003; Harrison & Mason, 2007).

The mean capital raised before joining the program is approximately $500 thousand in Canadian dollars, which is close to the USD$304 thousand among AngelList startups (Bernstein *et al.*, 2017). The average revenue of CAD$150 thousand is substantially higher than that of startups in U.S. accelerators reported in Cohen *et al.* (2019a). However, this difference is mainly driven by the skewed nature of performance in high-growth settings.

The $2.2 step-up in pre-money valuation of startups is relatively high. For instance, in their sample of 1,066 U.S. startups, Ewens *et al.* (2018) show a step-up of $2.24 million over eight years. Therefore, my sample of startups is likely higher quality than the average firm funded in the U.S.

A.4 Strategic Behavior in Mentoring Decisions

Do mentors select startups to minimize information asymmetry with potential investment targets rather than based on their ability to help them achieve their objectives? In settings like SEP, where mentoring decisions are visible, opportunistic behavior can entail reputational costs (see Gneezy *et al.*, 2011). These costs are expected to limit strategic behavior (Ariely *et al.*, 2009), especially where reputation underlies long-term success (Sorenson & Stuart, 2001; Gompers & Lerner, 1999).

Furthermore, investors can only signal higher value-added potential by providing better advice than the competition. In my setting this limits strategic behavior because the quality of advice is observable. Offering poorer advice undermines the perceived value-added potential of the investor, particularly for the high-quality startup the investor intends to learn about and potentially invest in.

Lastly, matching by expertise alleviates information asymmetry issues (Gompers & Lerner, 2001) more than matching by quality does. Investors rely on their expertise in assessing the risks and the promise of business ideas (Sørensen, 2007; Ewens & Rhodes-Kropf, 2015; Sorenson & Stuart, 2001), so aggregating judgment from multiple experts reveals more information about a future investment's potential than aggregating judgment from non-experts. Others have observed that investors do indeed cooperate in mentoring to improve startup ecosystems, which ultimately enhances the pipeline of investable companies (Miller & Bound, 2011).

A.5 Program Tracks

From the 2012-13 to 2014-15 program years, SEP was a single-track program with a cohort size of 20 startups. Motivated by the rapid commercialization of neural networks-based machine learning techniques after the ImageNet 2012 competition, SEP introduced a specialized AI Stream to its 2015-16 program year. The AI Stream admits startups whose core technology is based on advances in artificial intelligence. Mentor composition also includes AI-related exited entrepreneurs, and angel and institutional investors who have experience funding AI startups. Additional streams were added in subsequent years. For example, the Health Stream includes mentors who have extensive experience building or investing in health-related startups.

To accommodate applicant startups that do not fit in any of the existing specialized categories, SEP maintains a stream referred to as "Prime," which admits all other startups that meet the requirements of being scalable, seed-stage, and science-based.

A.6 Quality of Business Objectives

To ensure consistency in the quality of objectives, objectives must be 1) measurable, 2) feasible, and 3) agreeable to founders.

The first requirement is to ensure verifiability: that the objective must be designed such that a member of staff can verify whether it is completed or not. The second requirement is to ensure accountability: that ultimately, it is the entrepreneur who must achieve the objectives. The final requirement is to fix scope: that larger milestones are broken up into small enough objectives that are feasible to achieve within two months.

SEP staff train founders on how to meet these requirements, and session moderators who are primarily business school professors instruct mentors before every session. If an objective does not meet the requirements, the moderator points it out for revision during the group discussions.

A.7 After Sessions

Shortly after a session, staff inform startups of the mentoring decisions and facilitate connecting founders to the mentors who have chosen to support them over the next eight weeks. In order to enforce follow through, Staff also track and report to program directors if mentors do not honor their commitments. Repeated reneging by mentors results in getting dropped from the program.

One week prior to each upcoming session, moderators receive a detailed briefing on the latest progress of each startup. This briefing includes such information as the name of specific mentors to call on for comments, starting with mentors who advised the startup during the previous eight weeks. This enables private information obtained from mentoring to be shared with all mentors before debating the firm's objectives for the next eight weeks.

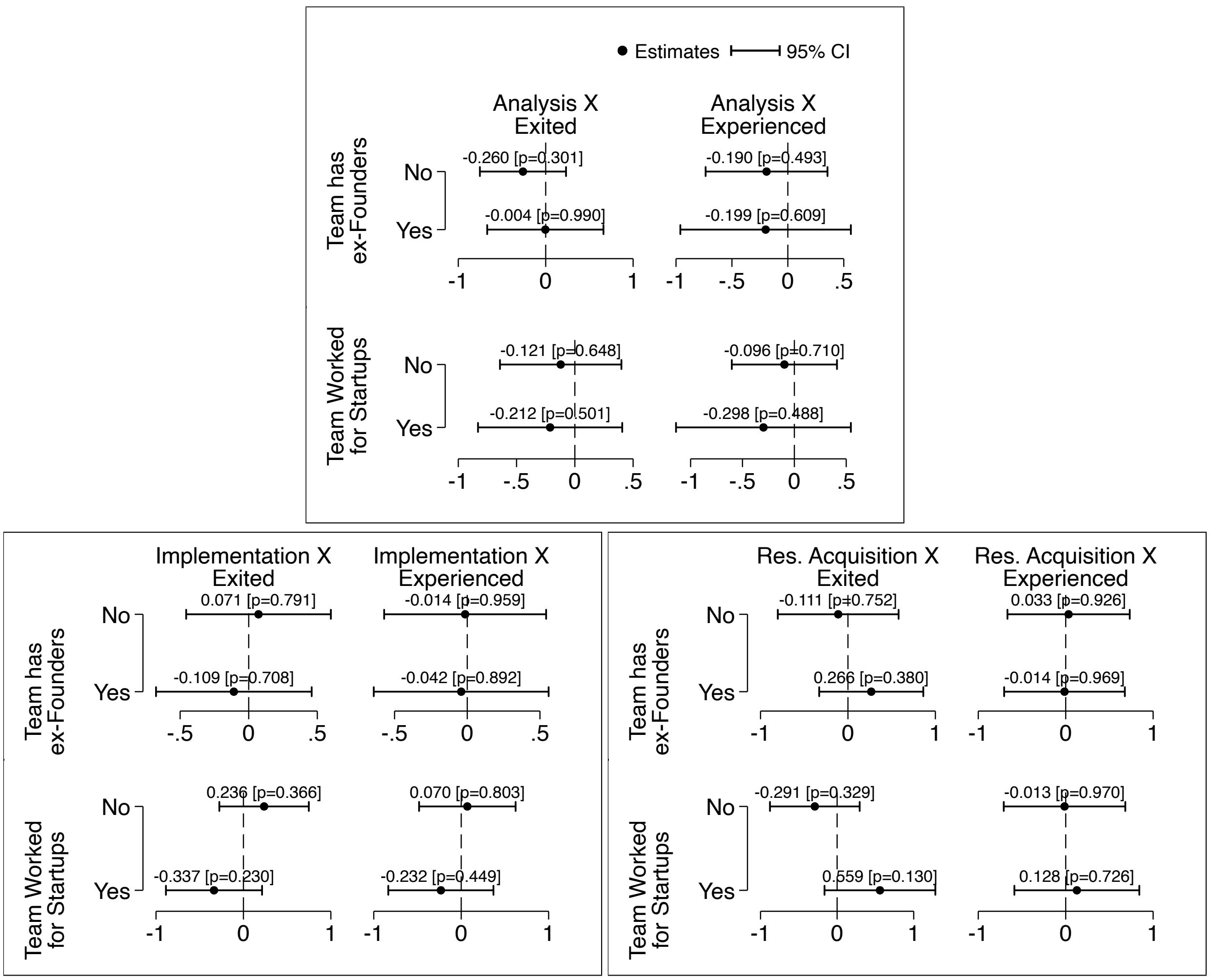
Appendix B Figures and Tables Appendix

Table B1: Sample Panel Data

Mentor i	Startup j	Session t	Mentor is Angel $Angel_i$	Priority is Experimentation $Experiment_{jt}$	Gave Advice $Advice_{ijt}$
041	1313	1	1	0	1
118	1313	1	0	0	0
213	1313	1	0	0	0
325	1313	1	0	0	0
365	1313	1	0	0	0
378	1313	1	0	0	0
391	1313	1	0	0	0
441	1313	1	0	0	0
908	1313	1	0	0	1
909	1313	1	1	0	0
911	1313	1	1	0	0
912	1313	1	0	0	0
913	1313	1	0	0	0
918	1313	1	1	0	0
118	1313	2	0	1	0
213	1313	2	0	1	0
325	1313	2	0	1	0
378	1313	2	0	1	0
391	1313	2	0	1	0
441	1313	2	0	1	0
908	1313	2	0	1	1
909	1313	2	1	1	0
911	1313	2	1	1	1
912	1313	2	0	1	0
912	1313	2	0	1	0
918	1313	2	1	1	1
920	1313	2	0	1	0
933	1313	2	1	1	0

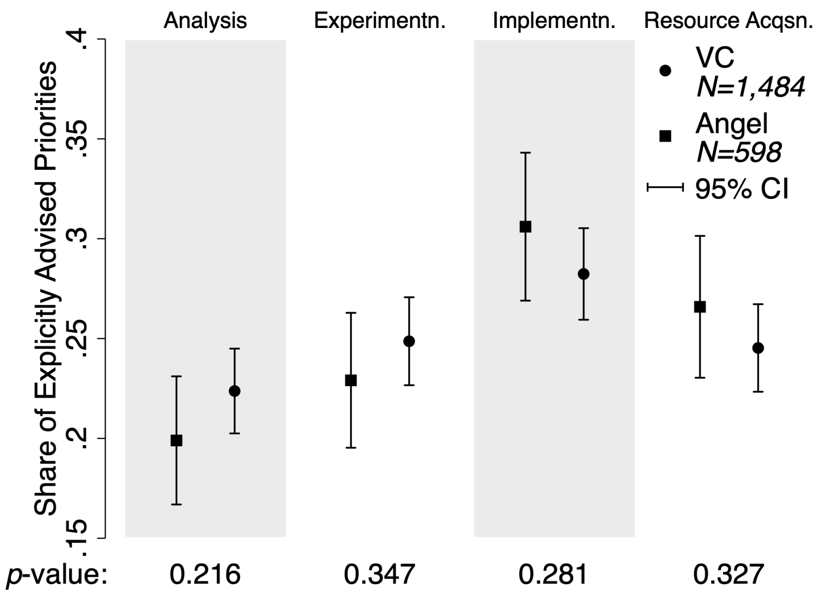
Notes: This table shows a slide of data on mentoring decisions of angels and VCs for a startup over two sessions.

Figure B1: Heterogeneity of Analysis, Implementation, and Resource Acquisition Advice by Founder and Mentor Experience: FE Logits



Notes: This figure shows point estimates and 95% confidence intervals for heterogeneity in different types of advice by founder and mentor experience. Team experience is measured as either prior founding experience (top row) or startup work experience (bottom row). Mentor experience is measured as either past exits (left column) or founding experience (right column).

Figure B2: The Explicit Advice of Angel Investors and Venture Capitalists



Notes: This figure shows the priority of each activity category, as explicitly advised by angels and VCs during one-on-one feedback sessions. These feedback sessions take place before the moderated meeting with all mentors.

Table B2: Comparing between the Typology of Early-Stage Startup Activities & Existing Classifications

Reynolds (2000)		This Paper	
Category	**Activity**	**Activity**	**Category**
Start-Up	Did you spend a lot of time thinking about this new business, or did the idea suddenly occur?	DNA (not an objective)	
	Has a business plan been prepared?	Develop Business Plan: a_6	Analysis
	Has a start-up team been organized?	Hire Co-Founder: a_{30}	Resource Acquisition
	At what stage of development is the product or service this start-up will be selling?	DNA (Not an objective)	
	Have marketing or promotional efforts been started?	Do Marketing: a_{24}	Implementation
	Has an application for a patent, copyright, or trademark relevant this new business been submitted?	License, Patent IP: a_{33}	Resource Acquisition
	Have any raw materials, inventory, supplies, or components for the start-up been purchased?	Dev. Production Capability: a_{21}	Implementation

Have any major items like equipment, facilities, or property been purchased, leased, or rented for the new start-up?	Dev. Production Capability: a_{21}	Implementation
Has an effort been made to define the market opportunities by talking with potential customers or getting information about the competition?	Conduct Market Research: a_1	Analysis
Have projected financial statements, such as income and cash flow statements or a break-even analysis, been developed?	Dev. Financial Plans, Models: a_4	Analysis
Are you now saving money to invest in this business?	DNA (Pre-entry/Unobserved)	
Have you invested any of your own money in this business?	No Equivalent (Unobserved)	
Have financial institutions or other people been asked for funds?	Raise Money: a_{34}	Resource Acquisition
Has credit with a supplier been established?	Dev. Production Capability: a_{21}	Implementation
Have your arranged child care or household help to allow yourself time to work on the business, either formally or informally with friends and relatives?	DNA (Unobserved)	
Have you begun to devote full time to the business – 35 or more hours per week?	Hire Co-Founder: a_{30}	Resource Acquisition

	Have any employers or managers been hired for pay – workers that would NOT share ownership?	Hire Employees: a_{31}	Resource Acquisition
	Has a bank account been opened exclusively for this new business?	DNA (pre-entry objective)	
	Has the new business received any money, income, or fees from the sale of goods or services?	Grow Sales, Customers: a_{25}	Implementation
	Have you taken any classes or workshops on starting a business?	DNA (Pre-entry objective)	
Firm Registration	Does the new business have its own listing in the phone book?	DNA (Unobserved)	
	Has the new business paid any state unemployment insurance taxes?	DNA (Unobserved)	
	Has the new business paid any federal social security taxes (FICA payments)?	DNA (Unobserved)	
	Has the new business filed a federal tax return?	DNA (Unobserved)	
	To your knowledge, is the new business listed with Dun and Bradstreet, the credit rating firm?	DNA (Unobserved)	

Bennett & Chatterji (2019)		This Paper	
Category	**Activity**	**Activity**	**Category**
Learning	Discussed the idea with a friend	DNA (Pre-entry objective)	
	Searched to see if someone already offers the product	Conduct Market Research: a_1	Analysis
	Consulted with an expert you knew	Conduct Market Research: a_1	Analysis
	Consulted with an expert you did not know yet	Conduct Market Research: a_1	Analysis
	Explicitly considered how other firms might respond	Conduct Market Research: a_1	Analysis
	Built a prototype or pilot	Build Prototype, MVP: a_{15}	Experimentation
	Tested demand	Do Demo, Pilot, POC: a_{11} Obtain Letter of Intent: a_{12} Quantify Value Proposition: a_{13} Validate ProductMarketFit: a_{14}	Experimentation
	Collected feedback from pilot to change business idea	Develop Business Plan: a_6	Analysis

Admin	Created a presentation, executive summary, etc.	DNA (Several objectives)	
	Built a website for the business	Build Organization: $a_2 0$ (See definition in table B3)	Implementation
	Created spreadsheets, financial models, etc.	Dev. Financial Plans, Models: a_4	Analysis
	Wrote a business plan	Develop Business Plan: a_6	Analysis
	Registered the business (for a tax ID)	DNA (Pre-entry/Unobserved)	
Other	Made a sale	Grow Sales, Customers: a_{25}	Implementation
	Explored financing options with a bank, etc.	Raise Money: a_{34}	Resource Acquisition
	Applied to an incubator/accelerator program	DNA (Unobserved)	
	Researched the legal or tax implications	Determine Regulatory Reqs: a_3	Analysis
	Explored using IP	License, Patent IP: a_{33}	Resource Acquisition
	Hired an employee	Hire Employees: a_{31}	Resource Acquisition

	Quit your job to work on the proposed business	DNA (Pre-entry objective)	

Carter *et al.* (1996)		This Paper	
Category	**Activity**	**Activity**	**Category**
Discriminating Activities	Bought facilities, equipment	Build Organization: a_{20} Dev. Production Capability: a_{21}	Implementation
	Got financial support	Raise Money: a_{34}	Resource Acquisition
	Developed models/prototypes	Build Prototype, MVP: a_{15}	Experimentation
Other precursor activities	Organized start-up team	Hire Co-Founder: a_{30}	Resource Acquisition
	Devoted full time	Hire Co-Founder: a_{30}	Resource Acquisition
	Asked for funding	Raise Money: a_{34}	Resource Acquisition
	Invested own money	DNA (Pre-entry/Unobserved)	

Looked for facilities/equipment	DNA	
Applied license/patent	License, Patent IP: a_{33}	Resource Acquisition
Save money to invest	DNA (Pre-entry/Unobserved)	
Prepared plan	Dev. Financial Plans, Models: a_4 Dev. Sales, Mktng Strategy: a_5 Develop Business Plan: a_6 Develop Hiring Plan: a_7 Develop IP Strategy a_8 Prepare for Financing: a_9	Analysis
Formed legal entity	DNA (Pre-entry objective)	
Hired employees	Hire Employees: a_{31}	Resource Acquisition
Rented facilities, equipment	Build Organization: a_{20} Dev. Production Capability: a_{21}	Implementation

Table B3: Definitions of Action Classes

Action	Definition	Exclusions	Examples
Conduct Market Research	Research or define the addressable market opportunity. Includes initial surveying of potential customers.	Late-stage feedback with pilot customers, demos and prototypes (see "Validate Product Market Fit").	Define a customer profile (persona) and customer success criteria. Typically intended to identify the appropriate target market, including understanding the barriers to entry, competitive landscape, industry trends, and corporate relationships.
Conduct Product Research	Define use cases of the technology. Specify target problem(s). May overlap with "Conduct Market Research".	Future development plans of the product and the user journey process (see "Develop Product Roadmap"). User interview feedback (see "Validate Product Market Fit").	Define requirements of the MVP. Understand the main value proposition for identified target customer segment(s).
Determine Regulatory Requirements	Identify requirements for a legal approval or compliance.	IP related requirements (see "Develop Intellectual Property Strategy").	Determine data privacy compliance. Identify regulatory pathways (i.e., 510(k) vs. De Novo). Collaborate with regulatory bodies (e.g., FDA).

Develop Financial Plan	Evaluate current or projected financial state.	Preparing for dilutive or non-dilutive funding (see “Prepare For Financing”).	Project revenues and expenses. Prepare budget projections. Calculate ROI, CAC or LTV. Determine cash runway.
Develop Revenue Model	Determine how product(s) will be monetized.	If analysis includes cost, see “Develop Financial Plan”.	Develop commercialization strategy. Understand the unit economics and how revenue is generated.
Develop Pricing Strategy	Establish a pricing model for product(s) and customer segment(s).	None.	Determine unit cost and desired margins. Research price of comparable products in the market.
Develop Sales and Marketing Strategy	Plan for how to market, sell and deliver the product.	None.	Define customer acquisition strategy. Develop sales playbook. Establish growth KPIs (e.g., international expansion). Determine market entry point. Understand distribution channels. Determine marketing strategy, branding, and messaging.
Develop Business Plan	Understand key business objectives and document how they will be achieved.	Specific planning activities (see “Develop Pricing Strategy”, “Develop Sales And Marketing Strategy”, and “Develop Financial Plan”).	Develop a business plan. Present a long-term business outlook. Set company key performance indicators (KPIs).

Develop Hiring Plan	Determine staffing requirements. Plan for future hiring and onboarding.	None.	Develop human resource plans or hiring strategies. Draft HR policies. Define roles and responsibilities.
Develop Intellectual Property Strategy	Define the IP and how it is or will be protected. May overlap with “Develop Regulatory Requirements”.	None.	Understand viability and defensibility of IP (may involve lawyers).
Prepare For Financing	Prepare for dilutive or non-dilutive funding.	None	Create funding strategy or prepare due diligence documents. Identify potential investors. Determine size of the financing round. Clean up the cap table.
Develop Technology Roadmap	Outline future technology development requirements and plans.	Future product development plans (see “Develop Product Roadmap”).	Determine future product feature requirements. Create project plan (resourcing, timelines, technical milestones).

Develop Product Roadmap	Outline future product development requirements and plans.	Future technology development plans (see “Develop Technology Roadmap”).	Determine future product feature requirements. Create project plan (resourcing, timelines, technical milestones).
Do Demo	Demonstrate the product.	None.	Develop or present demo. Demonstrate user experience.
Do Pilots	Conduct a pilot project with potential customers.	Clinical trials (see “Validate Technology”).	Obtain or sign a pilot contract. Engage with early customers for a pilot.
Do Proof Of Concept	Conduct a POC engagement with potential customers.	None.	Complete POC data package from current project.
Obtain Letter Of Intent	Obtain purchase or pilot commitment from potential customers.	None.	Obtain Expressions of Interest (EOI), Letter of Intent (LOI) or Master Service Agreements (MSA).
Quantify Value Proposition	Define the value proposition.	None.	None.

Validate Product Market Fit	Establish existence of a widespread set of customers that resonate with the product (Ries, 2011).	Technology validation (see “Validate Technology”).	Validate market-desirability and feasibility of the product. Validate stated value proposition. Gather product feedback.
Build Prototype	Develop embodiment of critical elements of the intended design (Lauff, 2018). May overlap with “Build Minimum Viable Product”.	None.	Enhance communication, enable learning, and inform decision-making in design process by building a prototype.
Build Minimum Viable Product	Develop a product with minimum effort and features (Ries, 2011). May overlap with “Build Prototype”.	None.	Gain key insights, measure customer response, or determine the need for pivot.
Validate Regulatory Process	Validate hypothesized regulatory processes.	Prepare documentation for a regulatory meeting (see “Determine Regulatory Requirements”).	Verify regulatory reimbursement pathways with regulatory bodies or consultants.

Validate Technology	Test technical functionality and feasibility of the technology.	White Papers as they are not peer-reviewed (see “Do Marketing”).	Conduct clinical trial. Establish efficacy. Validate externally or via peer-reviewed journal publication.
Choose Market	Pick the target market to pursue.	None.	Pivot to a new vertical. Choose a beachhead market.
Modify Pricing	Change the pricing model.	None.	Change price for specific product(s) or customer(s). Add pricing tiers. Adjust the profit margin.
Develop Sales Processes	Develop a repeatable sales workflow.	None.	Add sales tools and automation. Provide sales training. Set sales SOPs.
Build Organization	Set up a functional aspect of the firm.	None.	Incorporate the business. Appoint BoD. Determine vision of the firm. Set up office space. Create an org chart.

Develop Production Capabilities	Increase production throughput or capacity.	None.	Develop soft or hard production capabilities. Improve current manufacturing infrastructure.
Form Partnership	Establish strategic relationships with an entity that is not a customer or investor.	Pilot project with potential customers (see "Do Pilots").	Establish a partnership agreement, JDA, or MOU with a university, channel distributor, or OEM.
Deliver Product	Bring the product to end-users' hands.	None.	Deliver updated product to customers. Deploy a solution. Complete a technological integration. Complete manufacturing current order.
Do Marketing	Conduct marketing activities.	None.	Create marketing material (videos, white papers, collateral). Launch marketing campaign. Obtain marketing analytics.
Generate Sales	Generate revenue or sales. May overlap with "Get New Customers"	Acquire new customers (see "Get New Customers").	Close sales deals. Increase recurring revenue. Build a sales pipeline.

Get New Customers	Obtain a new customer.	None.	Convert a pilot customer (contract) to sales. Generate or secure meeting with a sales lead. Onboard new users. Sign contracts or POs with new customers.
Develop Technology	Develop the core technology.	Productize the technical development into a product (See “Build Product”)	Train a ML model. Develop protein folding algorithm.
Build Product	Build a fully-functional product.	None.	Convert the prototype into a market-ready product. Finalize the user interface.
Improve Product	Implement changes that improves the product. May overlap with “Develop Technology”.	None.	Iterate on existing features. Add new features. Scale existing features. Improve product performance.
Launch Product	Release a validated beta or public product to market.	None.	Release the product to initial users. Launch a new service offering.
Obtain Regulatory Approval	Obtain approval from a regulatory body.	Define regulatory requirements (see “Determine Regulatory Requirements”).	Establish compliance with laws and regulations. Submit an application to a regulatory body (e.g. FDA, EMA). Submit a REB application.

Hire Advisors	Recruit (paid or unpaid) business or technical advisors.	Board of Directors (see “Build Organization”).	Recruit key opinion leader (KOL), mentors, consultants, expert scientists, and technical or scientific advisors.
Hire Co-founder	Recruit a co-founder.	None.	Develop a shortlist. On-board a new co-founder.
Hire Technical Staff	Hire technical employees with specific STEM skills.	None.	Hire software engineers, chemists, or AI experts.
Hire Business Expert	Hire non-technical employees with professional expertise.	None.	Hire a sales, business development, customer success, marketing, operations, finance, or product expert.
Hire Employees	Hire employees with no specified expertise.	HR (see “Hire Business Expert”), IT (see “Hire Technical Staff”).	Address staffing needs.
Hire Executive Officers	Hire a member of the C-Suite.	CTO (see “Hire Technical Staff”).	Hire a CFO, CMO, COO, and CSO.

Get Data	Acquire data for software purposes.	Understand user engagement (see “Conduct Product Research” or “Conduct Market Research”). Acquire data for testing (see “Validate Technology”)	Acquire data from pilots, clients, partners or vendors.
License Technology	License IP.	Evaluate technology transfer options (see “Determine IP Strategy”). License technology to a partner or customer (see “Generate Sales”).	License technology from the patent holder. Transfer IP rights from university to the firm.
File Patent	Submit a formal patent application.	Develop a patent strategy (see “Develop IP Strategy”).	Draft the application and patent assessment with a lawyer. Convert a provisional patent to full utility. Complete prior art searches.
Raise Money	Acquire dilutive or non-dilutive funding.	None.	Acquire funds for operations or growth. Secure lead investors. Book meetings with investors. Negotiate term-sheets and valuation.

Table B4: Summary Statistics of Business Objectives

	Proposed $N = 2{,}271$	Finalized $N = 2{,}271$	t-statistic
Conceptual Categories			
Analysis	0.18	0.24	5.45
Experimentation	0.22	0.26	2.71
Implementation	0.36	0.28	−5.27
Resource Acquisition	0.24	0.22	−2.19
Tasks			
Analysis			
Market Product Research	0.06	0.09	3.90
Planning (Financial, IP, Sales, Reg.)	0.10	0.13	3.34
Product, Technology Roadmap	0.02	0.02	0.87
Experimentation			
Product Market Fit Validation	0.14	0.16	2.59
Tech, Regulatory Validation	0.09	0.10	0.82
Implementation			
Market Selection, Sales Processes	0.02	0.03	1.53
Organization Building	0.08	0.07	−1.26
Sales and Marketing	0.14	0.10	−3.64
Tech Dev., Approval, Launch	0.11	0.08	−3.97
Resource Acquisition			
Hire Employees, Advisors, Co-Founders	0.08	0.07	−2.16
License, Patent IP; Obtain Data for ML	0.03	0.03	1.29
Raise Money	0.13	0.12	−1.74
Activities			
Market Product Research			
Conduct Market Research	0.04	0.06	3.81
Conduct Product Research	0.01	0.02	2.16
Determine Regulatory Reqs.	0.01	0.01	−0.58
Planning (Financial, IP, Sales, Reg.)			
Dev. Financial Plans, Models	0.03	0.02	−0.68
Dev. Sales, Marketing Strategy	0.01	0.01	0.83
Develop Business Plan	0.01	0.02	3.13

Develop Hiring Plan	0.01	0.01	0.16
Develop IP Strategy	0.01	0.01	1.99
Prepare For Financing	0.04	0.06	2.30
Product, Technology Roadmap			
Dev. Product, Tech Roadmap	0.02	0.02	0.87
Product Market Fit Validation			
Do Demo, Pilot, POC	0.07	0.07	−0.06
Obtain Letter Of Intent	0.02	0.03	0.67
Quantify Value Proposition	0.00	0.01	2.20
Validate Product Market Fit	0.04	0.06	2.99
Tech, Regulatory Validation			
Build Prototype, MVP	0.03	0.03	0.28
Validate Regulatory Process	0.00	0.01	2.20
Validate Technology	0.06	0.06	0.06
Market Selection, Sales Processes			
Choose Market	0.00	0.00	0.78
Develop Sales Processes	0.02	0.02	1.33
Organization Building			
Build Organization	0.03	0.03	0.53
Dev. Production Capability	0.02	0.02	−0.78
Form Partnership	0.04	0.03	−1.84
Sales and Marketing			
Deliver Product	0.01	0.01	−1.92
Do Marketing	0.01	0.01	−1.49
Grow Sales, Customers	0.11	0.09	−2.81
Tech Dev., Approval, Launch			
Develop Technology, Product	0.09	0.06	−3.99
Launch Product	0.02	0.01	−1.56
Obtain Regulatory Approval	0.01	0.01	0.69
Hire Employees, Advisors, Co-Founders			
Hire Advisors	0.01	0.01	0.84
Hire Co-Founder	0.00	0.00	1.51
Hire Employees	0.07	0.05	−3.07
License, Patent IP; Obtain Data for ML			
Get Data	0.01	0.01	1.14

Table B5: Probability of Advice on Different Objectives by Angels vs. by VCs: Univariate Tests

	Angel Investor	Venture Capitalist	t-statistic
Panel A: Mean(Priority) Conditional on Advice			
Analysis	0.67	0.80	-2.24^{**}
Experimentation	0.87	0.69	3.19^{***}
Implementation	0.84	0.81	0.61
Resource Acquisition	0.62	0.71	-1.70^{*}
Panel B: Prob(Advice) Conditional on Priority			
Analysis	0.08	0.13	-2.82^{***}
Experimentation	0.22	0.10	5.58^{***}
Implementation	0.12	0.11	0.12
Resource Acquisition	0.12	0.11	0.17

Notes: Panel A shows the mean priority of activity types conditional on receiving advice from angels versus from VCs. Panel B shows the probability of receiving advice by angels and by VCs conditional on whether each of the four activity types were the firm's highest priority. Statistical significance is *(10%), **(5%), or ***(1%).

License, Patent IP	0.02	0.02	0.75
Raise Money			
Raise Money	0.13	0.12	−1.74

Notes: This table shows the average priority of different activities among proposed versus finalized objectives. The last column shows the t-statistic from difference in means tests for proposed and finalized priority of each activity type.

Table B6: Robustness of the Main Results to a Linear Probability Specification and Alternative Measures of Experimentation

DV = Advice Measure of Experiment:	(B6-1) Top Priority (binary) OLS	(B6-2) At least one (binary) FE Logits	(B6-3) Count (0-3) FE Logits
Experiment	-0.043^{***}	-0.055	-0.127^{***}
	(0.010)	(0.075)	(0.048)
Experiment × Angel	0.144^{***}	0.324^{*}	0.466^{***}
	(0.025)	(0.171)	(0.104)
Revenue Positive	-0.010	-0.091	-0.086
	(0.013)	(0.127)	(0.126)
AbvMed Funding	0.011	0.110	0.110
	(0.010)	(0.101)	(0.102)
Open Round	0.012^{*}	0.115^{*}	0.112
	(0.007)	(0.068)	(0.069)
Startup FE	Yes	Yes	Yes
Mentor FE	Yes	Yes	Yes
N	7,914	7,914	7,914

Notes: This table shows robustness tests for the main results shown in Model 4-2 of table 4. Model B6-1 estimates eq. (1) as a linear probability model, Model B6-2 redefines $Experiment_{jt}$ as an indicator equal to 1 if at least one of the top-three priorities is to experiment, and Model B6-3 redefines $Experiment_{jt}$ as the number of experiments prioritized. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

Table B7: Angel vs. VC Information Preferences: OLS

	(7-1) DV = Advised Priority of Analysis	(7-2) DV = Advised Priority of Experimentation
Angel	-0.038	-0.077
	(0.098)	(0.086)
Prob($\hat{\beta}_{\text{Angel Exp Pref.}} > \hat{\beta}_{\text{Angel Anlz Pref.}}$)		0.812
Startup × Session FE	Yes	Yes
N	579	579

Notes: This table regresses the number of analysis and experimentation objectives that mentors advised startups to prioritize on whether the mentor is an angel or a VC. Angels may perceive experimental signals as more informative than analysis. This may explain my results because angels preference for mentoring experiments would derive from a taste for experimentation, rather than a skill advantage in that domain. If, relative to VCs, angels find experimentation more informative, then they should also advise startups to prioritize it higher. To investigate, I codify transcribed notes from one-on-one meetings where mentors explicitly advise founders on which objectives to prioritize for the next eight weeks. Models B7-1 and B7-2 regress the number of analysis and experimentation objectives that mentors advised startups to prioritize, respectively, on an indicator that equals 1 if the mentor is an anagel, and zero if a VC. Both models include Startup×Session fixed effects to limit the variation from startups that receive advice from both an angel and a VC at a given session. The p-value of the χ^2 test of the difference between coefficient estimates is close to 1, meaning that angels and VCs are quite aligned on the relative importance of analysis and experimentation objectives. fig. B2 provides a visual summary of this result. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

Table B8: Angel vs. VC Stage Preferences: OLS and FE Logits

	FE Logits DV = Mentorship		OLS DV = Mentorship	
	(B8-1) Early-Stage	(B8-2) Late-Stage	(B8-3) Early-Stage	(B8-4) Late-Stage
Panel A: Revenue Generating				
Experimentation × Angel	0.690***	1.813***	0.090***	0.238***
	(0.225)	(0.329)	(0.031)	(0.043)
N	4,983	2,931	4,983	2,931
Panel B: Above-Median Funding				
Experimentation × Angel	0.944***	1.230***	0.125***	0.157***
	(0.226)	(0.325)	(0.031)	(0.043)
N	4,413	3,501	4,413	3,501
Panel C: Has Prototype				
Experimentation × Angel	0.957***	1.548**	0.129***	0.171**
	(0.189)	(0.635)	(0.027)	(0.073)
N	5,815	2,099	5,815	2,099
Startup FE	Yes	Yes	Yes	Yes
Investor FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: This table shows the main results conditional on startup stage. Compared to angels, VCs may prefer to work with later-stage startups, given their documented preference to fund later-stage deals (Gompers & Lerner, 2001; Kerr *et al.*, 2014a). If experimenting is more prevalent in earlier stages of a firm's development, angel versus VC propensity to mentor experiments may be an artifact of stage preferences. To investigate, I evaluate the robustness of my results across subsamples of earlier- versus later-stage seed-stage startups. I proxy for stage based on 1) revenue status, 2) capital raised, and 3) whether the startup has a functioning prototype. table B8 shows that my main results remain robust across early- and late-stage startups. Specifically, I re-estimate in subsamples of early- and late-stage startups using both fixed effect logits and linear specifications. It is worth noting that the magnitude of the experiment effects is generally larger for later-stage startups. This is consistent with the learning-by-doing explanation. Insofar as experimentation requires skills developed via learning-by-doing, and later-stage experiments are more complex to design and execute, angels' operational experience should play a more salient role in mentorship for later- than for earlier-stage companies. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).

Table B9: Ex-ante Sorting between Angels and Startups
FE Logits

	(B9-1) DV = Match	(B9-2) DV = Mentorship
Experiment	–0.068	–0.466***
	(0.156)	(0.121)
Experiment × Angel	0.688***	1.109***
	(0.238)	(0.194)
Match		2.220***
		(0.103)
Startup FE	Yes	Yes
Mentor FE	Yes	Yes
ℓ	-1,570.4	-2,148.8
N	7,914	7,914

Notes: This table examines the sensitivity of the main results to ex-ante sorting between angels and startups. Mentors are more likely to fund startups that they know (Sorenson & Stuart, 2001; Hochberg *et al.*, 2007). This would affect my results if angels are more familiar than VCs with startups that are in an experimentation phase. In my setting, prior to deciding which startups to mentor, each mentor meets privately with some startups but not others. At these meetings, mentors learn about startups' businesses and latest progress. Because these private meetings are determined by staff, it is possible that startups prioritizing experimentation are more frequently scheduled to meet with angels than with VCs. To examine this, I codify from the schedules of events a dummy variable *Match* that is equal to 1 if the mentor has privately met the startup, and zero otherwise. table B9 shows that my results are robust to the level of mentors' familiarity with startups. The estimated interaction in Model B9-1 suggests that entrepreneurs who prioritize experimentation are indeed more likely to be matched with angels than with VCs for private one-on-one meetings. However, Model B9-2 shows that even after controlling for this prior familiarity, my main results continue to hold. Standard errors clustered by startup are reported in parentheses. Statistical significance is *(10%), **(5%), or ***(1%).