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Organizational Resource Assembly in Technology Ventures

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Abstract
This dissertation addresses the assembly of organizational resources by technology ventures. We study how innovative firms acquire human and financial capital and then organize those resources, and how public policy affects that capability.

In the first chapter, we study the role of information in organizational decision-making for the financing of entrepreneurial ventures. We formally model a decentralized set of agents who vote strategically to allocate resources to a project with unknown outcome; they can each acquire costly information to improve their decision quality. We test our predictions in the setting of venture capital, where partners make their own angel investments outside of their employer. We find that the venture capital partners, acting independently, make riskier investments into younger firms with less educated and younger founding teams, but these investments perform better on some metrics even when controlling for investment size and stage. Geographic distance and liquidity constraints increase the probability the investment is taken up by a partner and not the VC.

In the second chapter, we evaluate the impact of skilled immigration on U.S. innovation by exploiting a random lottery in the H-1B visa program. Proponents argue that immigration allows firms to access technical skills and promote innovation, while opponents argue that firms substitute domestic labor for cheaper but equally or less skilled foreign labor. We find that winning an H-1B immigrant does not significantly increase patent applications or grants at the firm level, and there is pervasive use of the program in industries where patenting is not the main value-appropriation strategy.

In the third chapter, we study how a firm should organize the diversity of technical experience, contained within its pool of inventive human capital, for firm-level innovation. Using a sample of biotechnology start-ups, we examine the implications of alternate firm-level design regimes, drawing on both a firm-year panel structure and an inventor-year difference-in-differences empirical approach. Organizing a firm's human capital with greater across-team diversity yields increased firm-level innovation benefits as compared to organizing with greater within-team diversity. The benefits of across-team diversity stem mainly from the influence of that regime on team stability.

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Andy Wu

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Being deeply loved by someone gives you strength,

while loving someone deeply gives you courage.

— Laozi

This dissertation is dedicated to

Sail away from the safe harbor.

Catch the trade winds in your sails.

Explore. Dream. Discover.

— Mark Twain

my mother,

The important thing in life

is not the triumph,

but the struggle;

the essential thing is

not to have conquered,

but to have fought well.

— Pierre de Coubertin

my father,

If everything seems under control,

you're just not going fast enough.

—- Mario Andretti

and my sister.

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behavior and psychology for understanding social phenomenon.

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In the first chapter, we study the role of information in organizational decision-making for the financing of entrepreneurial ventures. We formally model a decentralized set of agents who vote strategically to allocate resources to a project with unknown outcome; they can each acquire costly information to improve their decision quality. We test our predictions in the setting of venture capital, where partners make their own angel investments outside of their employer. We find that the venture capital partners, acting independently, make riskier investments into younger firms with less educated and younger founding teams, but these investments perform better on some metrics even when controlling for investment size and stage. Geographic distance and liquidity constraints increase the probability the investment is taken up by a partner and not the VC.

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Table of Contents

List of Tables

List of Illustrations

Chapter 1

Organizational Decision-Making and Information: Angel Investments by Venture Capital Partners

Andy Wu

1.1 Introduction

Why do we trust groups to make some of our most important decisions? US criminal cases are determined by the unanimous vote of a jury, and a board of directors has the power to hire and fire the CEO by a majority vote. Why not one juror or one director? When preferences are aligned, groups can deliver superior decision quality relative to that of a single agent (de Condorcet, 1785) because of their ability to aggregate information across agents. Information aggregation represents an important differentiating capability for organizations (Cyert and March, 1963; Gavetti et al., 2007), and it is thus relevant to understand the optimal organizational structures that enable this capability and their associated boundary conditions (Csaszar, 2012).

In the setting of entrepreneurial finance, optimally aggregating information is especially crucial for financial intermediaries because information is low and at a premium. Entrepreneurial ventures lack any of the capital assets or organizational infrastructure present in larger incumbent firms, and thus they are difficult to value using straightforward explicit information: these ventures may have unproven management teams, enter new and undefined market segments, and develop cutting edge but untested technology products (Aldrich and Fiol, 1994). The lack of explicit information is further exacerbated by information asymmetry that results from entrepreneurs having greater access to information about their firm than outside parties (Dessein, 2005). As a result, non-traditional tacit information, such as "gut feel" about an entrepreneur or industry, play a large and pivotal role in the decision-making process in entrepreneurial finance (Huang and Knight, 2015; Huang and Pearce, 2015). To facilitate capital investments into these entrepreneurial firms, we have dedicated financial institutions, such as venture capital firms, angel investors, crowdfunding platforms, and accelerators, which seek to address these information problems and invest in high risk, high reward ventures. These institutions specialize in identifying investment opportunities from a vague choice set, acquiring and aggregating external information to evaluate and execute investments, and monitoring their investments ex post.

We study two particular organizational forms in entrepreneurial finance, venture capital firms and angel investors, which differ starkly in their decision-making structures. Venture capital firms are administrated by a general partnership. The partners individually source investments and collect intimate information about those investments through due diligence, which they then bring to the whole partnership for consideration. The venture capital partnership then makes decisions by committee through a formal or informal vote on the deals brought in. Angel investors also individually source investments and collect information, but unlike a venture capital firm, they make the investment decisions by themselves. Basic voting theory suggests that committees can more effectively aggregate information among informed parties than the parties acting individually (de Condorcet, 1785), so all else equal, we might expect a group decision-making process to outperform an individual decision-making process.

We examine a particular phenomenon where the information aggregation advantage of the venture capital organization may break down: individual angel investments by partners of venture capital firms. Partners of some venture capital firms make their own angel investments into ventures their firm ultimately chooses not to invest in. As a requirement of employment with the venture capital firm, the partners have a fiduciary duty, a *duty of loyalty*, to the venture capital firm. As such, the venture capital firm must always have the right of first refusal on any possible deal, and the partners can only invest in deals that the firm would not do. Thus, we observe angel investments made by the venture capital partners that were necessarily rejected or "passed over" by the firm decision-making criterion while meeting the partner's personal criterion for an investment. Between 2005 and 2013, over 500 US venture capital firms have partners who made such angel investments on the side. We ask why an individual partner would still pursue a deal when her colleagues, whose opinion she presumably respects, voted against it. It is a paradox and open question as to why a partner would take on substantially more personal financial risk to pursue her own investment.

To explain this phenomenon, we argue that there is a tradeoff in group decision-making between the benefits of information aggregation and the cost from the participation of uninformed agents, driven by a disincentive to acquire costly tacit information about the venture among the individual agents. This tension presents a fundamental boundary condition for group decision-making, namely that in some cases of heterogeneous information, the group decision underperforms an individual decision.

We offer a stylized formal model to explain the observed phenomenon. A committee of agents with homogenous utility functions must make a dichotomous choice about whether to invest in a particular project that can turn out to be good or bad. A sourcing agent receives a costless private signal, representing tacit information, which is costly to the other members of a committee. The agents all share a public signal component representing explicit information. The other agents have the option to acquire the private signal at cost; this decision is endogenous to the model. The committee then engages in a voting process with a pre-determined threshold. For the model, we find there is no pure strategy equilibrium where all agents acquire the costly private signal, but we find there is an equilibrium where some or no agents acquire the costly private signal. The comparative statics of the model generate a number of empirical hypotheses to test. First, projects funded by an angel investor will exhibit weaker explicit characteristics than those funded by the VC. Second, projects funded by the angel investor will have a higher associated cost to acquire the necessary tacit information. Third, projects funded by the angel investor will have less informative tacit information.

We test our theory on a large sample of investments made by venture capital partners, in the form of individual angel investments, and their employing firms, in the form of traditional venture capital investments. We find that the venture capital partners, acting independently, make investments into younger firms with less educated, less experienced, and younger founding teams, but these investments perform similarly or better on some financial metrics even when controlling for investment size, stage, and industry. Geographic distance and VC inexperience in an industry category increase the probability the investment is taken up by a partner and not the VC.

This project makes a number of contributions across the strategy and finance literature. This work is the first to document the investment patterns of venture capital affiliated angel investors, and it also contributes to the still relatively small literature on angel investors, who normally represent a heterogeneous and difficult group to study. Second, we are among the first large sample empirical studies of committee decision-making and one of the only to make some inroads into the micro-structure of the organization itself. Most of the prior work has been conducted in lab experiments (Kotha et al., 2015) and simulations (Csaszar, 2012). Third, we contribute to an emerging stream of work studying specialized decision-making structures as part of a "behaviorally plausible, decision-centered perspective on organizations" (Gavetti et al., 2007). Finally, the particular empirical setting at hand in this study is thematically related to work on spin-outs, companies founded by former employees of incumbent firms (e.g. Klepper, 2001), which we will discuss in the conclusion.

This paper proceeds as follows. In Section 1.2, we begin by presenting a stylized model for organizational decision-making with costly tacit information acquisition, and we derive empirical hypotheses from this model. In Section 1.3, we review institutional details about the organizational forms of venture capital firms and angel investors. In Section 1.4, we explain our particular empirical setting of venture capital partners who make angel investments. In Section 1.5, we detail the data and variable construction. In Section 1.6 and Section 1.7, we explain the empirical methodology and discuss the empirical findings. In Section 1.8, we conclude and link our work to related literatures.

1.2 Stylized Model

A primary purpose of the firm is to acquire, integrate, and then apply information for its productive use in the form of knowledge (Grant, 1996).[1] In the setting of venture capital, nearly all venture capital firms have a formal or informal mechanism, usually a vote, held for aggregating information from its partners when evaluating a possible deal. This information aggregation structure has direct implications for the ability of the organization to receive knowledge, in other words, its absorptive capacity (Cohen and Levinthal, 1990).

A key challenge for the organizational use of information is the transferability of said information. *Explicit information* is easily and credibly transferable, functioning as a public good. Explicit information can be costlessly aggregated by the organization since it is easily transferable. Examples of explicit knowledge relevant to the venture investor include educational characteristics and work experience of the founding team and the prior financial performance of the startup and its chosen market (e.g. Bernstein et al., 2016), facts that would be easy to record and communicate. Entrepreneurs create business plans and financial statements for the purposes of communicating this explicit knowledge to investors, and investors can share these documents amongst themselves to communicate this explicit knowledge with each other.

On the other hand, *tacit information*[2] (Polanyi, 1966) cannot be codified and is

[1] Information is often thought of as the antecedent to knowledge ("all that is known"), where knowledge is information in a useful cognitive representational form, such as a mental model, schema, rules, constraints, etc.

[2] Tacit information is also known as *implicit information*. We use tacit information as an umbrella

only revealed by its application, and thus its transfer between people is costly (Kogut and Zander, 1992). Tacit information plays a key role in the decision process for venture investors (Huang and Knight, 2015). Examples of tacit information include the investor's trust in the entrepreneur's character and intuition about future market trends, which are acquired through direct interaction with the entrepreneur or long-term personal experience respectively. The social psychology literature has focused on intuition, affectively charged judgements that arise through rapid and non-conscious associations between different ideas, as a major component of decision-making at the individual level. For example, Huang and Pearce (2015) show that "gut feel", a blend of analysis and intuition derived from the interpersonal relationship between the individual investor and the entrepreneur, has a real effect on investor decision-making. Indeed, the investor's intuitive assessment of the entrepreneur and other informal channels of information often make up the most important component of the investor's decision-making process, more so than the formal business plan (Huang and Pearce, 2015; Kirsch et al., 2009). Furthermore, symbolic actions, such as professionalism, and other factors gleaned through personal interaction play a deep role in venture investor decision processes (Zott and Huy, 2007). Thus, an important component of the information used by investors to evaluate early stage ventures is captured in this tacit information, and the ability to utilize this tacit information is a key source of competitive advantage for venture investors who are able to optimally utilize it.

This distinction in transferability of information presents a key inefficiency in simple group decision-making processes like voting. When all information is explicit, information can be shared among all participants and thus participants will be informed when they vote. When there is tacit information, some of the agents in a

construct spanning both cognitive and affective domains. Polanyi (1966) argues for the existence of tacit information by noting that "individuals know more than they can explain".

group may not acquire that information because the information acquisition process is individual costly to each agent. In a standard voting mechanism with no abstentions, agents who have not acquired the costly tacit information will still vote but vote in an uninformed fashion, making their vote worse than useless as they dilute the quality of the group decision that would have occurred without them. We henceforth refer to the explicit information as being *public*, since it is shared by all agents, and we refer to the tacit information as being *private*, since it is private to each agent and not shared. This choice of terminology is made to better align with norms in game theoretic formal modeling.

We propose a formal model to elucidate on the boundary conditions of group decision-making through a voting mechanism when some information is heterogeneous or costly to individual agents. For a committee voting by majority rule, where the voters are equally informed (all information is public), the Condorcet jury theorem says that adding more voters asymptotically increases the probability the decision will be correct (de Condorcet, 1785). However, we consider the case where there is heterogeneity in information available to the members of the committee by modeling the tacit component of information as an endogenous outcome of the model (Persico, 2004). We represent shared explicit information through a public signal, and the non-sharable tacit information is represented by a private signal.[3] The committee decision then notably deviates from efficiency and optimality. The primary channel by which agents can credibly express their opinion in a voting environment is through their vote. In most settings, every agent's opinion counts equally, but not every agent voting may be informed. This challenge sets up the primary theoretical tension at the heart of our theory: the benefit of aggregating information across the agents of

[3]The term *signal* has a different meaning here than in the labor market literature such as in Spence's 1973 work. The information content of the signal is only known to the focal agent.

the group versus the cost of participation of uninformed agents. We propose that this tension, driven by the introduction of costly private (tacit) information into the model, results in the VC partner angel investing phenomenon. We proceed with our model to show the existence of equilibria demonstrating this trade-off and to derive a set of comparative statics for the purposes of empirical testing.

1.2.1 Model Setup

We model a committee of three agents $i \in \{1, 2, 3\}$ who together represent the venture capital (VC) firm. The VC firm is responsible for making a dichotomous decision $x \in \{0, 1\}$, where 0 denotes "not invest" and 1 denotes "invest", on a project that is brought to the firm by one of the three agents, agent $i = 1$, and this agent is referred to as the *sourcing agent*. There are two states of the world for the investment, $s \in \{0, 1\}$, where an investment proves unprofitable in state 0 and proves profitable in state 1. The state of the world is unknown to the agents. Each agent i casts a vote $v_i \in \{0, 1\}$, where 0 is a vote against investing in the project and 1 is a vote for investing in the project. Each person's vote has the same weight. The committee requires a majority (at least 2 votes in favor) to invest in the project. If the committee does not invest in the project, then the sourcing agent can choose to invest in the project as an angel investor and independent of the VC firm.

1. **Sourcing** An agent belonging to the organization sources a possible investment and receives a public signal and a private signal, representing explicit information and tacit information respectively.

2. **Sharing** The sourcing agent brings the project to the organization if the combination of the public and private signal merits such, and the sourcing agent shares the public signal with the other agents.

3. **Acquiring Costly Information** Each of the other non-sourcing agents in the organization decides whether to acquire a private signal at a cost to them. This decision is conditional on the public signal brought by the sourcing agent.

4. **Voting** The agents vote. If the vote passes the predetermined majority voting rule, the organization invests in the project.

5. **Individual Decision** If the organization does not vote to approve the project, then the sourcing agent decides whether to individually invest in the project as an independent angel investor.

In evaluating a project and casting their votes, all agents have identical preferences, reflected by voting for the project if and only if their information is favorable. If the project is not funded, then each agent's payoff is 0, independent of state.[4] If the project is funded and the state is s, each agent receives a payoff of $U(s)$ where $U(0) < 0 < U(1)$. These payoffs are prior to subtracting any cost of acquiring information. For notational simplicity, we assume the payoff for the sourcing agent is also $U(s)$ when she makes an individual investment.[5]

Our model follows the setup and many assumptions of the jury voting literature (e.g. de Condorcet, 1785), and we use the notation as set out in Gerling et al. (2005). As is common in voting model literature and for all practical considerations, we only consider pure strategy Nash equilibrium and not probabilistic mixed strategy equilibrium.

---

[4] We assume there is no regret or loss aversion (Kahneman and Tversky, 1979) if the non-funded project is eventually funded by some other investor and proves successful. Relaxing this assumption may prove to be an interesting avenue for future work.

[5] If the VC firm does not fund the project but the sourcing agent does, then the latter's payoff is $\omega U(s)$ for some $\omega > 0$. $\frac{1}{\omega}$ can be interpreted as the proportion of the carry that is paid out to an investment partner at a VC firm for deals conducted through the firm. Given that theoretical results are robust to ω if utility is invariant to linear transformations, we can set $\omega = 1$ for the sake of reducing the amount of notation.

1.2.2 Information: Public and Private

Agents have two sources of information, explicit and tacit, represented in the model by a public signal and a private signal respectively. By definition, a public signal encompasses information that can be shared among the members of the VC firm, while the private signal contains information that cannot be shared. The public signal that the sourcing agent brings to the VC firm is embodied in the prior probability that the project will prove profitable: $\pi = Pr(s = 1)$. If agent i has a private signal, it is denoted $\sigma_i \in \{B, G, T\}$, which represent bad, good, and terrific signals respectively. To deliver the main hypotheses for the empirical analysis, the information space needs to more rich than the voting space; in other words, there must be more information than can be fully expressed by the voting mechanism. Since an agent has only two choices in voting $v_i \in \{0, 1\}$, it is sufficient to have three possible private signals. We define two of those signals as "favorable", where a signal is "favorable" if it increases the likelihood attached to $s = 1$ (investment in the project will prove profitable) and is "unfavorable" if it decreases the likelihood that $s = 1$. Signal B is unfavorable and both signals G and T are favorable. What distinguishes signals G and T is that G is not a sufficiently positive signal that, by itself, an agent would believe the project is worthy, while signal T is sufficient by itself for an agent to draw that conclusion. We will discuss this further in the next section when we define the conditions on expected utility.

The private signal σ_i has the following properties captured by the parameters q, θ, and β, which together with π define the information environment. q is the probability that the signal is favorable, $\sigma_i \in \{G, T\}$, when in the profitable state $s = 1$; q is also the probability that the signal is unfavorable, $\sigma_i = B$, when the state is unprofitable $s = 0$. Conditional on $s = 1$, θ is the probability that the signal is terrific $\sigma_i = T$ given the signal is favorable, $\sigma_i \in \{G, T\}$; analogously, conditional on $s = 0$, β is the probability that $\sigma_i = T$ given $\sigma_i \in \{G, T\}$.

$$\begin{aligned} Pr(\sigma = T|s = 1) &= \theta q & Pr(\sigma = T|s = 0) &= \beta(1-q) \\ Pr(\sigma = G|s = 1) &= (1-\theta)q & Pr(\sigma = G|s = 0) &= (1-\beta)(1-q) \\ Pr(\sigma = B|s = 1) &= 1-q & Pr(\sigma = B|s = 0) &= q \end{aligned}$$

In order for signals G and T to be favorable and B to be unfavorable, it is assumed that the favorable signals G, T are more likely when $s = 1$ than when $s = 0$ and the reverse is true for the unfavorable signal B:[6]

$$\begin{aligned} Pr(\sigma = G|s = 1) > Pr(\sigma = G|s = 0) &\Leftrightarrow (1-\theta)q > (1-\beta)(1-q) \\ &\Leftrightarrow \frac{1-\theta}{1-\beta} > \frac{1-q}{q} \\ Pr(\sigma = T|s = 1) > Pr(\sigma = T|s = 0) &\Leftrightarrow \theta q > \beta(1-q) \\ &\Leftrightarrow \frac{\theta}{\beta} > \frac{1-q}{q} \\ Pr(\sigma = B|s = 1) < Pr(\sigma = B|s = 0) &\Leftrightarrow 0 < 1-q < q < 1 \\ &\Leftrightarrow 1/2 < q < 1 \end{aligned}$$

It is assumed that $0 < \beta < \theta < 1$: conditional on a favorable signal, the signal is more likely $\sigma_i = T$ when the state is 1 than when it is 0. We have assumed symmetry in the signal, $Pr(\sigma \in \{G, T\}|s = 1) = Pr(\sigma = B|s = 0) = q$, so the signal provides the same information content about the state of the world in the profitable state and the unprofitable state. Finally, conditional on the state, agents' signals are assumed to be independent of each other.

The sourcing agent, denoted as agent 1, is assumed to already have the public and private signal and brings the project to the VC firm if and only if the private signal is favorable $\sigma_1 \in \{G, T\}$. If agent 1 brings the project to the VC firm, then the other two

[6]This assumption is equivalent to the monotone likelihood ratio property if the private signal were continuous.

agents will infer $\sigma_1 \in \{G, T\}$. Our model makes this assumption about the sourcing agent's signal to better reflect the realities of the deal flow process in a venture capital firm. In a venture capital firm, the partners of the firm are themselves responsible for sourcing deal flow for consideration by the firm. Beyond just the search process for possible investments, the partner conducts a due diligence process to assess the quality of the process, i.e. acquire the costly private signal. If a partner brought a project of poor quality, that would hurt the partner's reputation and waste the time and resources of the whole firm.

The initial information of agents 2 and 3 is just the public signal, represented by the prior probability $\pi = Pr(s = 1)$, and the knowledge that the sourcing agent has a favorable signal $\sigma_1 \in \{G, T\}$, although they do not know whether that favorable private signal is good or terrific. They will independently decide whether to acquire a private signal at a cost c which is born by the agent and not the VC firm. If agent 2 (or 3) acquires a signal and the project is not funded then her payoff is $-c$, and if it is funded and the state is s then her payoff is $U(s) - c$.[7] This costly information acquisition setup follows from Persico (2004).

After acquiring any private signals, the three agents simultaneously vote. The agents are not allowed to abstain.[8] It is assumed that agent $i \in \{1, 2, 3\}$ votes in favor of funding the project if and only if:

1. she acquired a signal and the signal is favorable $\sigma_i \in \{G, T\}$;[9]

[7] Presumably, agent 1 also faces the information acquisition cost, but it is assumed to be a sunk cost outside of this model.

[8] Allowing for abstentions would be an interesting extension on the model, but we do not believe that allowing for abstentions would change the general findings nor would it be a realistic assumption for the setting being studied.

[9] For this voting rule, an agent may vote for a project even if her current information does not indicate the project is profitable, merely that it has met the rule for being favorable. This action is perfectly reasonable given that the purpose of voting is to aggregate information, so there are cases where the group will find a project to be profitable even when the individual agent did not. This possibility is only feasible if those with favorable signals vote in support of the project.

2. she did not acquire a signal and based on her current beliefs she expects the project to be profitable.[10]

After outlining the expected utility conditions, we will characterizing the equilibrium for the information acquisition phase. we will show that this voting rule is optimal for those equilibria. We show that the voting rule is optimal in Appendix 1.A.4. The extensive form representation of the model is shown in Figure 1.1.

——————**Insert Figure 1.1**——————

1.2.3 Expected Utility Conditions

To ensure the existence of an equilibrium, we make the following assumptions with regards to the expected utility for the individual agents of the VC firm. The following assumptions ensure that the sourcing agent 1 brings projects to the committee for which she receives a signal $\sigma_1 \in \{G, T\}$, because they have a non-zero probabilities of being approved by the group, and that she would still pursue the project independently when she receives a signal of $\sigma_1 = T$.

1. $\mathbf{E[U] < 0}$ Without a private signal, the expected value of a project is negative:

$$E[U] = \pi U(1) + (1-\pi)U(0) < 0 \Leftrightarrow \pi < \frac{-U(0)}{U(1) - U(0)},$$

   and recall that $U(1) > 0 > U(0)$. Hence, the prior probability that the project is worthy of funding is sufficiently small. Given that the vast majority of ideas that come to a VC firm are not funded, this is a descriptively realistic assumption. For example, Andreessen Horowitz, a well-known venture capital firm, reviews over three thousand startups a year, and ultimates invests in fifteen.[11]

[10] We assume that the project is never profitable in expectation without having acquired the private signal.

[11] *The New Yorker* May 18, 2015 issue.

2. $\mathbf{E[U|\sigma = B] < E[U]}$ Signal B reduces the expected utility from funding the project:

$$
\begin{aligned}
E[U|\sigma = B] < E[U] \Leftrightarrow & \frac{\pi(1-q)U(1) + (1-\pi)qU(0)}{\pi(1-q) + (1-\pi)q} \\
& < \pi U(1) + (1-\pi)U(0) \\
\Leftrightarrow & q > \frac{1}{2}
\end{aligned}
$$

This assumption will justify voting against the project if an agent receives signal B. This parametric assumption has already been made in the model setup to ensure the private signal has informational value.

3. $\mathbf{E[U|\sigma = G] > E[U]}$ Signal G is favorable in that the expected utility is higher after having received this signal:

$$
\begin{aligned}
E[U|\sigma = G] > E[U] \Leftrightarrow & \frac{\pi q(1-\theta)U(1) + (1-\pi)(1-q)(1-\beta)U(0)}{\pi q(1-\theta) + (1-\pi)(1-q)(1-\beta)} \\
& > \pi U(1) + (1-\pi)U(0) \\
\Leftrightarrow & q(1-\theta) > (1-q)(1-\beta)
\end{aligned}
$$

This assumption will justify voting in support of the project if an agent receives signal G. Note that this parametric assumption has already been made.

4. $\mathbf{E[U|\sigma = T] > 0}$ Signal T is sufficiently positive that the expected utility of the project is positive:

$$
E[U|\sigma = T] > 0 \Leftrightarrow \frac{\pi q\theta U(1) + (1-\pi)(1-q)\beta U(0)}{\pi q\theta + (1-\pi)(1-q)\beta} > 0.
$$

This assumption will justify the sourcing agent funding the project if her only information is signal T.

5. $\mathbf{E[U|\sigma \in \{G, T\}] < 0}$ If an agent only knows a signal is favorable, but not whether it is G or T, then she will believe the project is not worthy of funding:

$$E[U|\sigma \in \{G, T\}] < 0 \Leftrightarrow \frac{\pi q U(1) + (1-\pi)(1-q)U(0)}{\pi q + (1-\pi)(1-q)} < 0.$$

Prior to deciding whether to acquire a signal, agents 2 and 3 have their prior beliefs and the knowledge that agent 1 received a favorable signal by virtue of having brought the project to the VC firm. At that moment, agents 2 and 3 have expected utility of $E[U|\sigma \in \{G, T\}]$ from funding the project. This assumption then implies that if they do not acquire the signal, they vote no.

6. $\mathbf{E[U|\sigma = G] < 0 < E[U|\sigma_i = G, \sigma_j = G]}$ By this condition, one good signal is insufficient to conclude the expected utility from the project is positive but two good signals are sufficient to reach that conclusion. Note that $E[U|\sigma = G] < 0$ (Assumption 6a) is implied by the preceding two assumptions: $E[U|\sigma = T] > 0 > E[U|\sigma \in \{G, T\}]$. To ensure $E[U|\sigma_i = G, \sigma_j = G] > 0$ (Assumption 6b), it is assumed:

$$E[U|\sigma_1 = G, \sigma_2 = G] > 0 \Leftrightarrow$$
$$\frac{\pi q^2(1-\theta)^2 U(1) + (1-\pi)(1-q)^2(1-\beta)^2 U(0)}{\pi q^2(1-\theta)^2 + (1-\pi)(1-q)^2(1-\beta)^2} > 0$$

This condition provides motivation for the existence of the decision-making organization and the use of a voting rule to aggregate information. If a single G signal was sufficient to conclude the project is worthy then there would be no need to bring it to a committee for a vote and no need for agents to make their decisions as part of the organization in the first place. Thus, the organization would not need to exist.

Assumptions 1 through 6 are sufficient to characterize the equilibrium. We can further add an additional assumption for $E[U|\sigma_i = T, \sigma_j = B] < 0$ to cover all cases of voting by the organization and to cover the scenario where agent 1 receives a signal of $\sigma_1 = T$ and agent 2 acquires signal but receives $\sigma_2 = B$. This additional assumption implies that agent 1 would not pursue the deal on her own, but this assumption is not necessary for the model or its empirical predictions.

Parameter Restrictions

The original assumptions on the parameters are: $\pi \in (0,1), q \in (\frac{1}{2}, 1), 0 < \beta < \theta < 1$, and $q(1-\theta) > (1-q)(1-\beta)$. Augmenting these original assumptions with the additional restrictions from the six conditions just derived from our expected utility assumptions, we can identify the parameter space for which the model holds. The derivation is presented in Appendix 1.A.1.

Given that $\pi \in (0,1)$, $U(0) < 0 < U(1)$, and $q \in (\frac{1}{2}, 1)$, let $\phi_\pi = \frac{\pi}{1-\pi} \in (0, \infty)$, $\phi_U = -\frac{U(1)}{U(0)} \in (0, \infty)$, and $\phi_q = \frac{1-q}{q} \in (0,1)$. Our expected utility conditions require the following parameter restriction:[12]

$$\phi_\pi \phi_U < \phi_q < \begin{cases} \dfrac{1-\theta}{1-\beta} \\ \dfrac{\theta}{\beta}\phi_\pi \phi_U \\ \sqrt{\phi_\pi \phi_U} \end{cases}$$

The conditions containing θ, β are then satisfied when $\theta, \beta \longrightarrow 0$ and $\frac{\theta}{\beta} \longrightarrow +\infty$. In other words, the probability of receiving a terrific signal (under either state of the

[12]To cover the case of $E[U|\sigma_i = T, \sigma_j = B] < 0$, we can add the additional optional constraint that $\phi_\pi \phi_U < \frac{\beta}{\theta}$.

world) needs to be small, but the probability of terrific signal needs to be far greater in the profitable state than in the unprofitable state.[13]

1.2.4 Equilibrium for the Information Acquisition Game

Agents 2 and 3 simultaneously decide whether to acquire a private signal at cost c. Once any signals have been acquired, the three agents vote. It was assumed that agent $i \in \{1, 2, 3\}$ votes in favor of funding the project if and only if:

1. she acquired a signal and the signal is favorable, $\sigma_i \in \{G, T\}$;

2. she did not acquire a signal and based on her current beliefs she expects the project to be profitable.

We refer to an agent who has acquired the private signal as being *informed* and an agent who has not as being *uninformed*. While it is not directly revealed whether agent 2 and/or 3 are informed, the sourcing agent does knows whether the other non-sourcing agents are informed, because she is aware of the parameters forming the cost of information acquisition.

After characterizing the Nash equilibria for the information acquisition game, we will show that this voting rule forms a symmetric Bayes-Nash equilibrium. For this equilibrium, the voting rule is optimal and the agents vote sincerely (Austen-Smith and Banks, 1996; Persico, 2004), and the proof of the voting rule optimality is presented in Appendix 1.A.4.

First, we show that there does not exist an equilibrium with both agents 2 and 3 acquiring the costly private signal.

[13] A computational simulation finds a broad set of parameters for which the identified equilibria will hold.

No Equilibrium with Both Agents Acquiring a Signal

There is no Nash equilibrium in which both agents 2 and 3 acquire the costly private signal. The full proof is presented in Appendix 1.A.2, but the intuition for it is as follows.

We show that it is not optimal for agent 3 to also acquire a signal if agent 3 anticipates agent 2 acquiring a signal. By the specified voting rule, agent 3 anticipates agent 1 voting for the project (as agent 1 would not have brought the project to the VC firm unless $\sigma_1 \in \{G, T\}$ and by the voting rule, an agent with a favorable private signal votes in support of the project) and anticipates agent 2 voting for the project if and only if $\sigma_2 \in \{G, T\}$. If it turns out agent 2 has a favorable signal, both agents 1 and 2 will vote in support in which case the project will be funded irrespective of agent 3's vote. If instead $\sigma_2 = B$, then agent 1 will vote for and agent 2 will vote against and, in that situation, agent 3 is the *pivotal* vote.

Given agents 1 and 2 acquire signals, agent 3's vote is pivotal only when the other two agents split their votes, i.e. one received a favorable signal and the other an unfavorable signal. Given that signals are independent and the symmetry in the model, the beliefs of agent 3, conditional on agents 1 and 2 splitting their votes, are just her beliefs prior to any information acquisition. Given that it is assumed a single favorable signal is insufficient to find the project worthy of funding, for agent 3 to acquire a signal and then voting in favor when the signal is favorable could only result in funding a project that is not worthy. We conclude there are no equilibria where both agent 2 and agent 3 acquire the private signal.[14]

[14] Consequently, a larger group does not necessarily translate into a more efficient decision, because when the voting rule is a number less than the group size, the remaining agents beyond the voting rule threshold may choose to remain uninformed.

Equilibrium with One Agent or No Agents Acquiring a Signal

Consider a strategy pair in which agent 2 acquires a signal and agent 3 does not acquire a signal. For agent 3, we know from the preceding analysis that she will prefer not to acquire a signal, so her strategy is optimal. By the voting rule, she will vote against the project because she has expected utility of $E_3[U|\sigma_1 \in \{G, T\}]$ which is assumed to be negative.

Agent 2 expects agent 1 to vote for the project—agent 1 brought the project to the firm so he can assume that $\sigma_1 \in \{G, T\}$—and agent 3 to vote against it. Thus, agent 2 is the pivotal voter. If he does not acquire a signal then, like agent 3, he will vote against the project and, therefore, his payoff is zero. If he acquires a signal, his expected utility is

$$\begin{aligned}&\Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}]\\&\quad + \Pr(\sigma_2 = B|\sigma_1 \in \{G,T\}) \times 0\\&= \Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}].\end{aligned}$$

Thus, acquisition of the signal is optimal if and only if the cost of information acquisition c is less than a critical threshold $\widehat{c}$ equivalent to the above expression, which is derived in full in Appendix 1.A.3.

$$\Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}] \geq c$$

$$\Leftrightarrow \widehat{c} \equiv \frac{\pi q^2 U(1) + (1-\pi)(1-q)^2 U(0)}{\pi q + (1-\pi)(1-q)} \geq c$$

If $c \leq \widehat{c}$, then it is optimal for agent 2 to acquire a signal given agent 3 does not. We already showed that for all values of c, it is optimal for agent 3 not to acquire a signal given agent 2 does. In summary, if $c < \widehat{c}$, then it is a unique Nash equilibrium for one of those two agents to acquire a signal and the other not to acquire a signal. If instead $c > \widehat{c}$, then it is optimal for agent 2 to not acquire a signal given agent 3 does not. By symmetry, we conclude that if $c > \widehat{c}$, it is the unique Nash equilibrium for both agents not to acquire signals.

For this equilibrium, the voting rule is optimal and the agents vote sincerely (Austen-Smith and Banks, 1996; Persico, 2004), and the proof of the voting rule optimality is presented in Appendix 1.A.4.

1.2.5 Theorems

This stylized model shows that the information aggregation benefits of voting in a committee can be offset by including endogenous individual costly information acquisition since uninformed agents continue to vote. We conclude the following:

Theorem 1 $\exists \widehat{c} > 0$ *s.t.*

(a) If $c > \widehat{c}$, the Nash equilibrium has agents 2 and 3 not acquire

(b) If $c < \widehat{c}$, the Nash equilibrium has agent 2 (or 3) acquire the signal.

When the cost of individual information acquisition is high, then the other agents without the endowed private signal are not incentivized to acquire the private information. When the cost of individual information acquisition is low, then one of the other agents will acquire the tacit information. Under Theorem 1a, the VC does not fund the investment, and the angel investor will fund it when $\sigma_1 = T$. Under Theorem 1b, the VC funds it when $\sigma_2 \in \{G, T\}$, and the angel investor does not fund it.

Theorem 2 *$\nexists$ an equilibrium in which both agents 2 and 3 acquire the private signal.*

Informally, there is no equilibrium where both agents 2 and 3 acquire the private signal because you only need as many informed agents as there are votes needed to reach the predetermined voting threshold. This particular theorem has no implications for our empirical study, but it is a matter of theoretical interest.

1.2.6 Empirical Hypotheses

Focusing on the critical threshold $\widehat{c}$ for the cost of acquiring information, we produce three testable empirical hypotheses.

First, we look at how $\widehat{c}$ changes relative to different levels of the public information π. We analytically show in Appendix 1.A.5 that the comparative statics of $\widehat{c}$ imply

$$\frac{d\widehat{c}}{d\pi} > 0$$

For larger π, there is a higher acceptable cost threshold $\hat{c}$. In other words, the acceptable cost of acquiring the private signal is increasing in the public information, or the baseline probability of a profitable investment. It is thus more likely that agents 2 or 3 will acquire the private signal and thus make it more probable that they would vote for the possible project. If we take the public signal representing explicit information to be characteristics observable to the econometrician, this result leads to the following hypothesis.

Hypothesis 1 *Projects funded by an angel investor will have lower π than projects funded by the VC. They will on average appear worse on observable characteristics.*

Observable characteristics include types of information that can easily and credibly transferred between parties.[15] In our setting, we will interpret that as easily observable characteristics of the firm and its founding team, such as the pedigree of the founders and the age of the firm.

Second, consider the relationship between c and $\widehat{c}$. Recall that if the cost c exceeds $\widehat{c}$, then none of the non-sourcing agents engage in costly information acquisition. In that case, the organization is certain to reject the project. When instead the cost of a signal is less than $\widehat{c}$, then it is still possible that the project may be funded.

Hypothesis 2 *Projects funded by an angel investor will have higher c than projects funded by the VC. They will on average have a higher cost of information acquisition.*

As noted before, tacit information is more costly (harder) to acquire than explicit information since it requires experiential contact between the investor and entrepreneur. We will use geographic distance between the investor and the entrepreneur as a proxy for the cost of information acquisition, as in Sorenson and Stuart (2001), who argue that information about potential investment opportunities generally circulates more within proximate geographic spaces. There is extensive work in both the teams (e.g. Clark and Wheelwright, 1992) and multinational (e.g. Ahearne et al., 2004) literature showing that distance increases the cost of information exchange. In our setting, the other partners of the VC organization will be less likely to acquire costly tacit information since it is more costly for the non-sourcing agents to visit the physical office and meet the full team of the venture, which only the sourcing agent would have already. Thus, they would be less likely to be informed and then less likely to invest as suggested by the model.[16]

[15]In the finance literature, this might be thought of as "hard" information, which is generally taken to mean quantitative type information (Petersen, 2004).

[16]There are also a number of cognitive and behavioral measures that may drive up the cost of information acquisition, but we omit discussion on that in this work.

Figure 1.2 presents the the implication of the public signal content and information cost for investment vehicle outcome as discussed in Hypothesis 1 and Hypothesis 2. For $\hat{c}(\pi)$ where $\frac{d\widehat{c}}{d\pi} > 0$, there is an equivalent relation $\hat{\pi}^{-1}(c)$. If $\pi > \hat{\pi}^{-1}$ then the VC invests. If $\pi < \hat{\pi}^{-1}$, then the angel investor invests.

————————**Insert Figure 1.2**————————

Third, the comparative statics presented in Appendix 1.A.5 also produce the result that

$$\frac{d\widehat{c}}{dq} > 0$$

For larger q, there is a higher acceptable cost threshold $\hat{c}$. In other words, the acceptable cost of acquiring the private signal is increasing in the information content of the private signal. It is thus more likely that agents 2 or 3 will acquire the private signal if the private signal is more informative.

Hypothesis 3 *Projects funded by an angel investor will have lower q than projects funded by the VC. There will be less information content in the private signal in investments done by the angel relative to those done by the VC.*

This result should be fairly intuitive, but unfortunately it is difficult to test in the data, since there is no clear empirical measure for a private signal, which is presumably private to to the researcher.[17] We empirically proxy for this by looking at the employing VC firm's experience in a given category (business model, technology method, or technology platform). Since tacit knowledge, represented by the private signal, is developed through experience (e.g. Lam, 2000), then it will be more informative for the other non-sourcing agents of the firm to evaluate the deal if they are already experienced in that category. For example, imagine an investor evaluating

[17] Tacit to the partners is still tacit to the econometrician!

a deal in the business model category of Software as a Service (SaaS). There are specialized aspects to evaluating that type of business that are developed experientially, such as predicting the product-market fit, knowing the optimal management style, and understanding key performance indicators[18] (e.g. annual recurring revenue, bookings, churn). These are all things that would be developed and honed through practical experience working with and investing in SaaS businesses, and thus tacit information would be more informative when an agent evaluates a future deal in the space.[19]

These are the three main hypothesises we will test empirically. We make no predictions about the distribution of financial performance between the angel investor and their employing VC, but we document performance metrics as a matter of empirical interest.

1.3 Organizational Forms in Entrepreneurial Finance

We focus our study on two organizational forms tailored to entrepreneurial finance, venture capital and individual angel investors.

1.3.1 Venture Capital Firms

Venture capital (VC) is a subset of private equity that originated in the 20$^{\text{th}}$ century designed to provide financing, usually equity financing, to early stage, high

[18] The reason that the key performance indicators for SaaS would not necessarily fall into costless information in the public signal is that the metrics are not actually true financial metrics (revenue, profit), but are meant to be taken as a whole and interpreted qualitatively.

[19] A primary endogeneity issue with this proxy is that if a VC firm is experienced in a given category, then they would also be more prepared to add value to the investment ex post via mentoring and advising. This effect would bias the results towards more venture capital investments and away from angel investments.

potential startup businesses. There is an extensive literature on the subject spanning the last three decades (e.g. MacMillan et al., 1986; Sahlman, 1990; Bygrave and Timmons, 1992; Hsu, 2004). Much like the broader category of private equity, which includes leveraged buyout and mezzanine type investments, venture capital firms in the United States are a financial intermediary, most commonly structured as a *general partnership*[20] composed of *general partners* who manage and invest the funds put up by *limited partners*,[21] which include public pension funds, family offices, and others. The venture capital firm raises money from limited partners in discrete funds that have around a 10 year lifespan before the money is returned to the outside investors, due to the illiquidity of the market for private equity in startup businesses. The general partners of the firm are paid through a *management fee*, a set proportion of the funds under management, and the *carry*, a percent of the profits, which are conventionally set at 2% and 20% respectively. In addition, the general partners have their own capital invested in the fund, usually representing around 1% of the fund.

The general partners have complete control over the day to day management of the limited partner fund.[22] Some subset of the partners, if not all of them, are investment professionals dedicated to sourcing, conducting due diligence (collecting information), decision-making, and executing investments into startups; after the investment, the venture capital firm works to add value to their investments through official channels

[20]The general partnership structure of venture capital firms provides tax advantages and is flexible with respect to allocation of losses and profits and management of the partnership. The partners are theoretically personally responsible for the liabilities of the general partnership, which does not include liability incurred by the fund itself, so liability risk is functionally irrelevant.

[21]The first venture capital limited partnership was established in 1958, because they were exempt from various securities regulations requiring disclosure. They soon supplanted the closed-end fund structure, which was publically traded and sensitive to the whims of finicky unsophisticated investors (Gompers and Lerner, 2004).

[22]Interestingly, venture capital firms have "virtually no general legal obligation to behave in the best interest of their investors" (Rosenberg, 2002). It is presumed that they act in the best interest of their investors, as acting otherwise may hurt their individual and group reputation and thus hurt their ability to raise future funds and accrue future profits.

such as board membership or unofficially through mentorship and advice, with the eventual goal of bringing the investment to an exit opportunity, namely an acquisition (M&A) or initial public offering (IPO) event. When we refer to partners in this paper, we specifically mean investment partners; other non-investment focused employees of the firm may carry the title of partner, but they are not included in the study. The composition of the general partners is of utmost important to the performance of the VC firm: Ewens and Rhodes-Kropf (2015) argue that the partners' human capital is two to five times more important than the VC firm's organizational capital.

By the time of the internet boom of the 2000s, nearly all domestic venture capital firms were structured as general partnerships, and the consequence is that venture capital firms have taken a less hierarchical structure to their operations than other kinds of businesses. The firms are small, with small numbers of partners and support staff. The partnership model has become so dominant that even in cases where the firm may not have to be legally structured as a general partnership, such as the case of corporate venture capital or non-U.S. venture firms, they often take the implicit non-hierarchical if not legally codified structure of a partnership, and will refer to members of their management team by the title of partner. Regardless of the legal structure,[23] the standard decision making process in this industry is non-hierarchal and jointly made by the de facto if not de jure investment partners in the context of a committee. We confirm and document the existence and role of this group decision-making stage through semi-structured interviews conducted with employees of 19 venture capital firms; a limited discussion of these interviews is presented in Appendix 1.B.1.

The relatively flat hierarchal structure has consequences for the deal sourcing

[23] As the Limited Liability Company (LLC) entity form has grown more popular across all types of businesses in the United States, many venture capital firms have taken this legal structure while still maintaining the partnership organizational form; the LLC entity has grown more popular since the firm can elect to implement the pass-through taxation of a partnership with the limited liability of a corporation.

process. Each investment partner is responsible for contributing to the deal flow by finding and bringing in possible investment opportunities. The potential deals are sourced by the partners themselves; the partners are assisted by more junior associates in larger firms, but a deal coming into the firm is generally associated with a particular partner. The partners source potential deals in a variety of ways, including introductions from their personal networks, solicitations from entrepreneurs with no prior connection to the partner, and public news (Hoyt et al., 2012; Shane and Cable, 2002). From the set of all investment opportunities she sees, the partner then pre-screens for the highest quality investments to select the set she would like to bring up for consideration by the full partnership.

Once it reaches the full partnership, the partners jointly make a decision on whether or not to act on the investment opportunity. The entrepreneur will be invited to present to the firm at the regularly occurring partnership meeting, which customarily occurs on Mondays. The sourcing partner will share her information with the rest of the firm and argue in favor of the investment. Since the perceived quality of the deal has career and financial implications for the sourcing partner, the sourcing partner will normally speak in favor of the potential deal as she will get pecuniary and reputational credit for it if the investment turns out to be a good one. Often, the sourcing partner will end up taking a board seat or advisory role in the startup if they invest. Since the other partners know that the individual partner will benefit from having her own deals executed, there may be some discounting of the partner's information, and the other partners will have to acquire their own information to make a fully informed judgment.

There are many reasons the firm may not invest. Other partners may decide the investment is of poor quality, for example if they were to believe it has too small a potential market size, has a weak management team, or lacks product-market fit.

This belief is likely in contrast with the belief of the sponsoring partner, who clearly believed the deal had merit. The other partners may have acquired their own private information on which to judge the investment, or they may not believe the information provided by the sourcing partner and also fail to acquire their own.

Some VC firms have an *investment thesis*, a formal or informal statement that jointly represents the firm's ex ante plan about the types of businesses they want to invest in. This investment thesis is based upon what the partners believe to be the best path towards reaching the ideal level of risk and return for their portfolio, based upon the information known to them when the thesis is written. The investment thesis may proscribe a number of target specifications on investment size, investment stage, industry, geography, and management team profiles.

An investment thesis is generally not legally binding, either to the general partnership entity or to any of its limited partnership funds. Thus, the VC firm can freely invest outside of the bounds of the thesis, and the majority of firms will do so. For example, Union Square Ventures's investment thesis states that they seek to invest in "large networks of engaged users, differentiated through user experience, and defensible through network effects."[24] They have invested in a number of startups that are only peripherally related or unrelated to that thesis, including enterprise drones and financial technology. The investment thesis represents an aspirational goal–and indeed the majority of the portfolio is related to the stated thesis–but it is by no means a requirement for venture capital firms.

1.3.2 Angel Investors

At the other end of the spectrum of organizational sophistication in entrepreneurial finance, there are individual investors, known as angels. There is a growing but rela-

[24]As described on the Union Square Ventures company page.

tively limited academic literature focusing on this form of financing.[25] Angel investors take on all the roles of the venture capitalist, including deal sourcing, pre-screening, evaluation, and then the final decision, all rolled up into one person. These angel investors are generally affluent, as they must be accredited by the securities commission of their home country: in the United States, an accredited investor must have a net worth of at least $1 million, not including the value of their primary residence, or they can have an income over $200,000 each year for the last two years (in other words, they have to have enough money such that they can afford to lose their money on their risky investments). Angels generally make equity or convertible debt investments, just like venture capitalists. Angel investors come from various backgrounds: many are current and former executives and entrepreneurs, while a smaller subset are pure full-time angel investors. Since angel investors use their own funds to make investments, they have less access to capital than a venture capital firm and make smaller investments; smaller investments happen earlier in a startup's lifecycle, so they often invest earlier than VCs.[26]

There is a small existing literature on angel investment that mostly focuses on the differences and conflict between angel investors and venture capitalists. On average, angel investors occupy a different niche in entrepreneurial finance, serving younger, less capital intensive startups (Lerner, 1998). Hellmann and Thiele (2014) study the interaction between angel and venture capital markets. Goldfarb et al. (2013) argue that angel objectives align more with entrepreneurs than VCs, and that outcomes may be linked to conflicts of interest; they find that deals with more angel investors have

[25]For example, Kerr et al. (2014) find in a discontinuity analysis that ventures backed by angels in syndicates have improved survival, exits, employment, patenting, Web traffic, and financing than those not backed.

[26]The term "angel round" has entered the parlance and is used to mean what might also be referred to as a seed round, which happens before a series A round. However, this terminology does not mean that angel investors do not participate in venture rounds, and they may also make venture sized investments.

weaker cash flow and control rights, and experience longer times to resolution. Larger deals financed by VCs alone are most likely to experience successful liquidation.

Angel investors have also been used as a setting to study individual decision making. Maxwell et al. (2011) find that angels use a shortcut decision making heuristic which they refer to as elimination-by-aspects to reduce the available investment opportunities to a manageable size. Huang and Pearce (2015) study the role of *gut feel* in angel investor decision making.

In this paper, we focus on a particular kind of angel investor: partners of venture capital firms. We refer to these individual investors as *angel partners*. By focusing on this subset of angel investors, we get around one of the empirical challenges with studying angel investors: they are by no means a homogenous group, and they vary heavily by skill, background, and personal motivation. As expected, there are substantial differences between the partners of venture capital firms and angel investors with other backgrounds. First, angel partners presumably still have access to the skills and professional network that they use while employed as a full-time venture capitalist. These skills can include deal evaluation (e.g. more experience looking at startups), deal execution (e.g. familiarity and access to the legal documents used by their employing firm), and post-deal value add (e.g. hiring support). Second, they see a lot more possible deals than a part-time angel investor, as they are compensated to look at deals full time. Thus, they have a larger pool of deals to choose from, even conditional on some of those deals going to their employer. Third, given their full-time employment in financial services, many of these angel partners are of ultra-high net worth and can make larger angel investments approximating a smaller venture investment in the seed, series A, or series B rounds.[27]

[27] Since an angel partner is likely wealthier than the average angel, she is also more capable of defending her fractional ownership share of the startup by using a contractual *pro rata* right to invest more funds in the next round of financing to maintain her original proportion of ownership.

The partners of venture capital firms are more sophisticated than the average angel investor on nearly all dimensions and comparable in process and performance to a venture capital firm. In Figure 1.3, we provide basic descriptive information generated from the Crunchbase data about that difference. VC affiliated angels, as compared to non-VC affiliated angels, make more investments, make larger investments, and participate in later funding rounds, but participate in similarly sized investment syndicates. In other words, angel partners make investments closer to and in the territory of venture capital firms.

1.4 Empirical Setting: Angel Investments by Venture Capital Partners

The particular empirical setting we study is perhaps best illustrated by an anecdote. C. Richard "Dick" Kramlich was a founding partner at New Enterprise Associates (NEA), which he founded in 1978 after leaving Arthur Rock and Co., where he began his career. An entrepreneur named Rob Campbell was seeking additional venture funds for his computer software company Forethought, Inc. He was working on a new program called Presenter, which generated text and graphics for overhead transparencies. The company was mired in a variety of logistical, engineering, and financial issues: the engineering on the product was delayed, their largest distributor went into Chapter 7 bankruptcy, and they were running out of investment money fast. They approached New Enterprise Associates for additional funds. The partners of NEA disagreed on whether to invest in Forethought—they were unsure about the company and they did not like Campbell either—and they ultimately decided not to invest. Dick wasn't ready to let it go so easily. He believed there was something special about the firm and its product, beyond what the current observable state of the firm would suggest. He asked his partners if he could pursue the investment on his own, with his own money. Since the investment was not in conflict with anything in the existing portfolio, they gave him the go ahead. He called his wife to tell her "Pam, stop work on the house. I'm going to fund this company myself". The company survived, and in early 1987 they renamed their main product "PowerPoint". In August of the same year, just four months later, Microsoft acquired ForeThought for $14m USD cash (1987 value), a lucrative exit for everyone involved. Microsoft eventually integrated PowerPoint into its Office suite of desktop applications, and the rest is history (Goldfine and Geller, 2011).

1.4.1 Conditions on Angel Investments by Partners

The identification of individual vs. group investment decisions comes from the phenomenon of venture capital firm partners and other employees who also make angel investments on the side with their own funds. As a requirement of employment with the venture capital firm, the partners have a fiduciary duty to the venture capital firm first. In legal terms, the partners owe a *duty of loyalty* to the partnership, and this duty requires all partners to disclose any potential opportunity that the partnership entity would potentially be interested in taking. They then have to wait until the partnership passes on the opportunity before they can personally engage on it.

Accordingly, the venture capital firm must always have right of first refusal on any possible deal, and the employee can only invest in deals that the firm would not do. In addition, the deal cannot be in conflict (i.e. in competition with) with any current investments already in the venture capital firm's portfolio and any probably future investments the firm expects to make. We should also note that not all venture capital firms allow their partners to make outside investments of their own,[28] so we do

[28] Bill Bowes at US Venture Partners has stated that they do not allow this (Goldfine and Geller,

not include the universe of venture capital firms. We only study venture capital firms that have partners who make angel investments, which is still represents a substantial proportion of venture capital firms.

We can observe investments made by the venture capital firm and those rejected by the venture capital firm and invested in by its partners through an angel investment. This empirical strategy partially addresses the risk set problem facing empirical work in venture capital: we normally cannot know what investments were rejected by the venture capital firm, and now we can observe at least a portion of them. As noted before, since there is so much heterogeneity among the general category angel investors, the sample gives us a better composed set of angel investors, who are skilled and have access to the same information and resources as VCs, and can be then directly compared to venture capital firms.

Our study still faces the two-sided matching challenges in much of the literature: we cannot officially discern whether the entrepreneur had any choice in whether to take the partner's personal angel investment or the VC firm's, but it is assumed that the entrepreneur would have to take the venture capital investment if offered, because the partner is not allowed to make a competing angel investment cross-bid.

1.4.2 Alternative Scenarios

There are plausible alternative stories for the partner angel investments we observe. In the most extreme case, the partner may withhold and hide potential investments from their employing firm or in a lesser form, she may intentionally undersell the quality of a deal if there is a certain "home run" investment opportunity and the partner wants to fully capitalize on the gains.

If the investment opportunity is withheld, the venture capital firm does not have

2011).

a chance to consider the investment, but our interviews with venture capital partners suggest this is highly unlikely. A partner acting otherwise would face the consequences of legal action by the firm and its limited partners (outside investors). Beyond direct legal consequences, there would be significant reputational costs that translate directly into future financial costs in an industry based heavily on network connections and syndication activity. The network of investors and entrepreneurs is fairly small and geographically concentrated, and secrecy would be difficult to maintain; additionally, the sample we study is only of publicly known investment events. While there is a possibility of incentive compatibility issues, both the formal legal barriers and reputational costs of hiding possible investments suggest it is highly unlikely and would not be a dominating factor driving the observed phenomenon.

In a related but weaker version of the withholding story, a partner may disclose but intestinally undersell the quality of an investment so that the VC firm will then pass it up and so the partner can capture it for herself. We cannot empirically rule out this possibility, but this story is still consistent with the theory we have proposed in Section 1.2. A partner that is underselling the quality of a deal does so by making the available public signal π artificially low by failing to disclose relevant explicit information to her partners. Hypothesis 1 states that a potential investment with lower π are more likely to be passed on by the VC firm and then be taken up by an angel partner.

Our model is agnostic to return proportionality: if a partner takes a deal on their own, then they stand to have more exposure to both the upside and downside of a potential deal since they capitalized on all the returns and not just the carry compensation from their VC firm. This proportionality does not change the sign of the risk-adjusted net present value of a possible investment. One could make an argument about the differential need for risk-return levels in a VC vs. an individual.

For example, perhaps the partners know that the VC needs high-risk high-return type investments, while angels can live with low-risk low-return type investments. While this is plausible true, the empirical results presented in Section 1.7 are not consistent with this story, as the angel partners invest in deals that are observable weaker, and presumably riskier.

In another case, the partner may fail to bring a potential investment to their employing firm if she does not believe that the firm will act on the potential investment. The partner may have prior information that suggests to her that the venture partners will likely vote no regardless and that bringing the investment up to a vote would be a waste of time and reflect poorly on her sourcing skills. For example, the potential investment may be in a sector that does not fit the traditional investment pattern of the venture capital firm, often codified as an *investment thesis* discussed in the prior section.[29] Let us assume that the partner is correct, and that the venture capital firm would indeed not act on the investment. Again, similarly to the extreme case, we interpret this again as the extreme case of where the partners share a low public signal, and therefore do not bother expending the cost to acquire private information. As another example, deals that are "too small," i.e. need only a small amount of capital, may not merit a full discussion by the firm and would be passed upon immediately because it would be perceived as not capital efficient by the firm. This possibility would still fit into the model, as there is likely a fixed cost to conducting due diligence on a deal (acquiring the private signal), and the possible profit from the deal would not be perceived as justifying the financial and cognitive costs of evaluating it.

[29] There is an interesting philosophical question here: if an investment is considered good enough that a partner would invest in it, is it really outside of the purview of the venture capital firm to make the investment? The investment ability of the firm is captured by the aggregate ability of the partners themselves, and the venture capital firm could simply structure its decision-making process to capture these deals by allowing the partners to make individual independent decisions on investments without the group decision stage.

Regardless, we agree that it would be more empirically interesting to compare deals that are clearly within the purview of the venture capital firm and the angel investor. We introduce a number of industry, investment size, and round characteristics to control for this, and we also estimate a matching model that directly addresses this issue.

1.5 Data

1.5.1 Sample Construction

The main dataset is constructed from the universe of venture capital and angel investment rounds from January 1$^{\text{st}}$, 2005 to December 31$^{\text{st}}$, 2013, as identified in CrunchBase. This set contains firms founded before and during the observation window, as long as they raised a round in our observation window. CrunchBase is a database of startup firms and affiliated people (employees, board members, etc.), financial organizations, and service providers. The database is operated by TechCrunch, a news website and AOL Inc. subsidiary focused on firms in the information technology sector; accordingly, the data oversamples firms in the IT sector relative to biotechnology and other industries. Much of the data, particularly on investment events, is entered by TechCrunch staff based upon their own reporting and SEC Form D filings. A large component of the data is *crowdsourced*: registered members of the public may make submissions to the database which are then reviewed individually by moderators working for TechCrunch. CrunchBase is also synced up with AngelList, a website for matching between startups and angel investors, giving us additional coverage of angel investments.

CrunchBase has superior coverage of angel investment events relative to the more traditional venture capital database of VentureXpert/Venture Economics (now part of ThomsonOne) used in much of the earlier venture capital literature (Bygrave, 1988; Gompers and Lerner, 2004). To check the coverage of CrunchBase data, Block and Sandner (2009) compared a sample of CrunchBase data with statistics published by the National Venture Capital Association (NVCA), and they find that the number of investment events in the CrunchBase data accounts for about 97% of the Internet-related deals as reported by NVCA (amounting to about 21% of all VC deals).

We identified all individual angel investors whose primary occupation is in a financial organization that has made an investment into a startup in our sample. We include investors even if they were employed at their financial organization for only a portion of our observation period, but this represents only a minimal portion of the sample. We only retain firms that were identified as either a venture capital, private equity, or angel stage investment firm, but we refer to these collectively as venture capital.[30] The final full sample consists of 879 unique individuals making investments out of 726 venture capital organizations into 8342 different startups. We construct the data at the investment-level, so each observation represents an investment by either the VC or the angel partner.[31]

[30]We classified each of these financial organizations into venture capital, private equity, corporate venture capital, angel investment firm, seed accelerator/business incubator, or a family office. The classification was made using information from the website of the respective firm. Venture capital firms were defined as those who have the stated strategy of investing in early-stage, growth startups and who manage money on behalf of outside investors (limited partners). Private equity firms were distinguished from venture capital firms as those that also made leveraged buyout, mezzanine capital, distressed, and secondary investments, although they could have also made traditional venture capital investments in our time period. Corporate venture capital is a venture capital firm making investments on behalf of a corporation that is not primarily engaged in investment. Angel investment firms specialize in making seed stage investments, either with funds directly held by the firm or by an outside limited partnership as in traditional venture capital. Seed accelerators and business incubators make fixed size investments and also offer participation in a fixed-term cohort-based program which may include office space and mentorship (in almost all cases). Family investment firms are those firms that primarily make investments on behalf of a single individual or family and are also managed by that individual or family.

[31]We also constructed a dataset that restricts the set of investments made by venture capital firms to those that are confirmed to be "approved" by the individual investors in our data. We identified "individually approved" investments by identifying investments where the focal investor "led" the investment into the venture and thus holds a board or executive position in the startup.

1.5.2 Entrepreneurial Venture: Observable Characteristics

To study the distribution of observable characteristics that make up the public signal in our theoretical model and thus test Hypothesis 1, we construct a number of entrepreneurial firm characteristics at the time of the investment event, primarily based upon characteristics of the founding team. The age of the startup at the funding round is taken as the number of days between the founding date and the investment round; a younger age is considered riskier because there is less of an explicit financial track record to evaluate the startup on. To identify the founding team, we identify individuals formally associated with the startup and who have listed themselves as a founder in their job title. Firms in about half our sample, for both venture capital investments and partner investments, disclose this information. For each founding team member, we build educational characteristics using CrunchBase profiles supplemented with public LinkedIn information to identify whether they have an MBA, a PhD, a regular masters degree, and if they attended an "elite" institution,[32] and whether or not they studied engineering. We then aggregate this to the firm level by identifying whether or not the founding team has at least one founder with a given educational characteristic and averaging the number of founders with a given education characteristic. We construct a measure of founder age by averaging over the imputed age of the founders, which we determine by making assumptions about their age given their graduation year.[33] We also study whether any of the founders

Unfortunately, this sample was omitted from the paper because a large amount of data was missing in a systemic way as to introduce bias: we cannot observe cases where the focal investor led the investment for the venture capital firm but did not take a position in the startup or did not publicly disclose it. We suspect that the public disclosure of the board member is a non-random choice by the investors.

[32] We identify "elite" educational institutions as those in the top 25 US national universities and the remaining top 25 non-US universities that were not in the US list, as defined by US News & World Report in 2015.

[33] Ages are assigned by assuming the founder is a certain age at the graduation year of the lowest degree they list. We assume a founder is the following age at graduation: high school is 18, bachelors degree is 22, master degree is 24, JD is 25, MD is 26, PhD is 27, and MBA is 30. All

have prior entrepreneurial experience and measure the count of previous startups the founding team established that received any equity financing.

1.5.3 Entrepreneurial Venture: Financial Performance

While we make no predictions about financial performance, differences in financial performance of investments by angel investors vs. venture capital firms is certainly of empirical interest and included for such reason. We construct a number of outcome variables to evaluate investment performance as commonly used in the entrepreneurial finance literature. We use future funding rounds as a proxy for firm survival, with measures of whether or not the firm achieves any future funding rounds and the count of future funding rounds. We gauge financial performance with dichotomous variables on the achievement of a merger and acquisition (M&A) event or an initial public offering (IPO). We also have exit valuations for all firms which underwent an IPO and for some of the firms undergoing an acquisition, i.e. for any case where the final exit valuation was publicly reported.

1.5.4 Controls

There are a number of controls and matching criteria that need to be implemented. First, angel investors tend to make smaller investments than venture capital firms, due primarily to liquidity constraints (the individual partner has less access to capital than his employing venture capital firm which has raised money from outside limited partners) but also due to both risk aversion (an individual angel investor faces full exposure to the loss). For a given amount of funds raised, a round composed of only angels tends to have more participants in the syndicate than a round composed only

ages are calculated for the year 2010, which is acceptable because we include year fixed effects in all empirical models.

of venture capital investors. Thus, we need to control for the size of the investment being made and the number of participants in the round. Unfortunately, the size of the investment of each participant in a syndicate is not available for most observations: we accordingly control for the size of the total round as a proxy for the size of the individual investment. Second, angel investors traditionally make investments into earlier stages of the venture lifecycle, so we introduce round fixed effects controlling for the particular stage of financing (seed, series A, series B, etc.). Third, we would like to broadly control for across-industry heterogeneity, so we classify each firm into a two digit North American Industry Classification System (NAICS) and introduce industry fixed effects. Fourth, venture capital activity tends to follow the business cycle (e.g. Gompers et al., 2008), so we introduce year fixed effects.

1.5.5 Information Acquisition Cost: Geographic Distance

To proxy for the cost of information acquisition and test Hypothesis 2, we look at the geographic distance between investments and their investors. We calculate geographic distance between venture capital firms and their investments by calculating the geodesic distance in kilometers between the two, i.e. the length of the shortest curve between two points along the surface of a mathematical model of the earth (Vincenty, 1975). Addresses of the venture capital firms and startups were collected from CrunchBase and their public facing websites. For the majority of firms, we only have either their zip code or their city, state, and country available: we assume they are located at the geographic center of the most specific address we have. Since at the within city level, our locations are only approximate, we left censor our data for any geodesic distance less than 1 km and round that to 1 km. In the case of firms that have multiple offices, we took the distance between the two closest offices, on the assumption that the closest offices are likely the ones interacting. In our analysis, we take the natural logarithm of the distance since the baseline distance measures are heavily skewed, and the resulting logged distance distribution is substantially closer to normal.

1.5.6 Tacit Information: VC Experience

To proxy for the information content of the private signal and test Hypothesis 3, we look at the experience of the venture capital firm in specific categories. On CrunchBase, each startup can self-designate itself into a number of keywords. We then focus on keywords placed into broad two digit NAICS codes which contain software, internet, and information technology firms.[34] Each of these self-descriptive keywords were classified into categories by business model, technology method, and technology platform. The business models are business-to-business (B2B), business-to-consumer (B2C), crowdsourcing, freemium, infrastructure as a service (IAAS), lead generation, licensing, machine-to-machine (M2M), open source, peer to peer (P2P), platform as a service (PAAS), and software as a service (SAAS). The technology methods are advertising, information aggregation, data analytics, artificial intelligence, big data, content management, crowdfunding, cyber security, e-commerce, gamification, gaming, local, media streaming, modeling, operating system, payment, productivity, sharing, and social media. The technology platforms are application, browser, cloud, mobile, package, and website. The categorizations are not mutually exclusive: a firm can fit into multiple categories if they list keywords that fit into multiple categories, but each keyword is filled into an exclusive category.

For a given VC-venture or angel partner-venture investment round, an experience measure is constructed for the investing or employing VC by taking the count of

[34] The main NAICS codes containing software, internet, and information technology firms are 33 Manufacturing, 42 Wholesale Trade, 44 45 Retail Trade, 51 Information, 54 Professional, Scientific, and Technical Services, and 61 Educational services.

investments executed by the VC prior to the date of the focal investment round in the category of the startup that is receiving investment. For ventures that fall into more than one category, we take the value of the category for which the VC has the most experience.[35]

1.5.7 Descriptive Statistics

Descriptive statistics for investment level data are presented in Table 1.1. We have a much larger sample of investments by the venture capital firms than we do for angel investments by their partners. Not unexpectedly, venture capital firms are on average making larger investments in older firms, at an average round size of $13.17 million and firm age of 1193 days while the angel partners invest at an average round size of $4.04 million and firm age of 569 days. However, the different in the round number is not as large as one might expect, where angel partners invest in an average round of 1.40 and the VC firms invest at an average round of 1.53. This difference is not very large for a couple reasons. First, the nature of the startup firm lifecycle is that there is a high death rate from round to round, so there are compositionally many more early round investments than later round investments by the VCs. Second, there are many venture capital firms that only do early stage investments, and these are usually the smaller VC firms which actually represent most of the sample of VCs. Thus, the high average round size and later firm age for the VC investments is driven by the presence of relatively few outlier large and late stage investments made by the VCs, which the angel partners cannot execute because they lack the financial capital to do so. We have limited data on the founding team characteristics, with data for about half the sample. A test of missing data on founding team characteristics is presented

[35]Empirical results are robust to taking the average experience over multiple categories for when the venture falls into multiple categories, instead of the maximum.

in Appendix 1.C.2.

———————Insert Table 1.1———————

1.6 Empirical Strategy

We propose empirical strategies to document the compositional differences between angel investments by VC partners and investments by their employing VC firm and provide evidence in support of the empirical hypotheses suggested by our theoretical model.

1.6.1 Main Model

To test Hypothesis 1 and to document differences in financial performance, we run an ordinary least squares (OLS) model with organization fixed effects and year fixed effects on the sample of investments we study. The organization fixed effects control for time-invariant effects common to the members of the venture capital organization and to the venture capital organization itself; the identification assumption being made here is that the angel investor and their parent organization share the same mean investment preferences and performance.[36] We can conceptualize that preference as skill to select investments that is now being controlled. We cluster standard errors by organizational affiliation. This full sample is where we choose to test our moderators.

For investment i by the firm or affiliated partner j at time t, we regress the dependent variable of interest on $Angel_{ijt}$, an indicator for whether the investment was taken by the partner (1) or the firm (0). $\bar{X}_{ijt}$ represents a vector of controls,

[36] This assumption may not universally hold if we believe that there is persistent heterogeneity in information access or skill by the partners, such as documented in Ewens and Rhodes-Kropf (2015).

including the size of the funding round and the count of the investors in the syndicate. α_j represents a fixed effect for the affiliated VC organization of the investment. δ_t represents a year fixed effect to control for the business cycle. ρ_i represents a round number fixed effect. τ_i represents an industry fixed effect, where industry is defined by the 2 digit NAICS code. β then is the coefficient of interest, and it shows the average compositional difference in the dependent variable DV_{ijt} between investments by a given VC and its angel partners, controlling for year, round, industry, round size, and syndicate size.

$$DV_{ijt} = \beta Angel_{ijt} + \gamma \bar{X}_{ijt} + \alpha_j + \delta_t + \rho_i + \tau_i + \epsilon_{ijt} \quad \text{(Main Model)}$$

We begin with the full set of angel investments by individual investors whose primary occupation is in a financial organization and the set of venture capital investments by the venture capital firms that employ these individuals.

1.6.2 Matching Model

To address the issues of confounding compositional differences between the angel partner and VC investments, such as differences in stage and industry, we introduce a matching model where we match each angel investment one-to-one with a venture capital investment made by their parent firm to further explore Hypothesis 1 and financial performance. The primary issue with the first specification is that financial constraints and investment theses limit the types of investments that can be made by individual investors with respect to venture capital firms. The venture capital firms have greater access to capital from their limited partners and thus can make larger investments, which often happen at later stages. Angel investments are usually limited to the earlier stages where the investors make smaller investments. The investment thesis of a firm may place an cultural and implicit–but not legally or officially binding–bound on the investments allowed within the venture capital firm. There are also numerically many more venture capital investments than angel investments in our sample. Starting with the full sample of angel partner investments, we match each angel investment with the venture capital investment that is in the same 2 digit NAICS class and closest in total round size and then round date, with a maximum of $1 million different in round size. We drop angel investments that do not have a match: these are cases where the venture capital firm makes very large investments relative to the size of the angel investments made by their employees, which are general venture capital firms making mezzanine or growth equity investments, which are closer to what is generally classified as private equity. We run a similar investment-level OLS regression as the full sample, and we use robust standard errors.

For investment i by matched pair $p \in P$ and at time t, we regress the dependent variable of interest on $Angel_{ipt}$ as defined before, controls $\bar{X}_{ipt}$ for round size and syndicate size, year fixed effect δ_t, and round fixed effect ρ_i.[37]

$$DV_{ipt} = \beta Angel_{ipt} + \gamma \bar{X}_{ipt} + \delta_t + \rho_i + \epsilon_{ipt} \qquad \text{(Matching Model)}$$

The summary statistics for the matching model are presented in Table 1.3.

——————Insert Table 1.3——————

Both the Main Model and the Matching Model analysis are meant to be descriptive and intended only to describe the compositional differences in characteristics and performance between venture capital investments and angel investments made their partners. By construction, the main independent variable of *Angel* is not causal in nature.

[37] Matched pair fixed effects can also be included, but it is unnecessary since the sample is balanced. Results are similar with the inclusion of matched pair fixed effects.

1.6.3 Geography Model

To test Hypothesis 2, we present a variation of the Main Model where the dependent variable is now whether the investment goes to the angel partner or stays within the VC, defined before as $Angel_{ijt}$. $\ln(D_{ij})$ represents the log distance (km) between the VC firm and the venture, and it is logged because the distances are heavily skewed and the log transformation makes it more appropriate for use in an OLS model. After preliminary tests, the non-monotonicity of the effect of geographic distance became obvious (see Figure 1.4 for a visual presentation), and accordingly a piecewise analysis of distance was deemed more informative. $D_{ij}^{[L,R)}$ is an indicator variable for whether the investment is between L kilometers and R kilometers away from the VC; indicators are created for the bounds $[100, 1000)$, $[1000, 10000)$, and $[10000, 100000)$. This model is still estimated in OLS clustered at the organizational level, but it is robust to other functional forms (probit and logit). These indicators are interacted with $\ln(D_{ij})$ to illustrate the effect of distance for each range of distance. The same vector of controls $\gamma\bar{X}_{ijt}$, organization fixed effects α_j, year fixed effects δ_t, round fixed effects ρ_i, and industry fixed effects τ_i are included as in the Main Model.

$$\begin{aligned}
Angel_{ijt} =& \beta_1 \ln(D_{ij}) \\
&+ \beta_2 D_{ij}^{[100,1000)} + \beta_3 \ln(D_{ij}) D_{ij}^{[100,1000)} \\
&+ \beta_4 D_{ij}^{[1000,10000)} + \beta_5 \ln(D_{ij}) D_{ij}^{[1000,10000)} \\
&+ \beta_6 D_{ij}^{[10000,100000)} + \beta_7 \ln(D_{ij}) D_{ij}^{[1000,100000)} \\
&+ \gamma\bar{X}_{ijt} + \alpha_j + \delta_t + \rho_i + \tau_i + \epsilon_{ijt} \qquad \text{(Geography Model)}
\end{aligned}$$

1.6.4 Category Experience Model

To test Hypothesis 3, we present a model similar to the Geography Model. The variables $BusModel_{ijt}$, $TechMethod_{ijt}$, and $TechPlatform_{ijt}$ represent the experience of the parent VC in the category of the investment as described in the data section. The other controls and fixed effects are the same as in Geography Model, with the exclusion of the industry fixed effects ρ_i.[38]

$$\begin{aligned} Angel_{ijt} = &\beta_1 BusModel_{ijt} + \beta_2 TechMethod_{ijt} + \beta_2 TechPlatform_{ijt} \\ &+ \gamma \bar{X}_{ijt} + \alpha_j + \delta_t + \rho_i + \epsilon_{ijt} \end{aligned} \tag{Category Model}$$

We test this model with both the full sample and a sample only containing investments for which the affiliated venture capital firm has non-zero experience in the respective category, to address concerns about the bounds of an investment thesis.

1.7 Results

1.7.1 Hypothesis 1: Explicit Information

We find evidence in favor of Hypothesis 1. Table 1.2 and Table 1.4 present the results on the analysis on observable venture characteristics with the Main Model and Matching Model respectively. We focus here on the discussion of the results of the main specification, but similar results follow in all samples. Coefficient signs generally hold throughout the models, but statistical significance suffers as we lose power in some of the subsample based models (round 1 and 2, matching).

[38]The model is robust to the inclusion of industry fixed effects. We choose not to include them here, because we only analyze the sample of software, internet, and information technology firms for which we can define categories.

—————————**Insert Table 1.2**—————————

—————————**Insert Table 1.4**—————————

We find that individual partners invest in firms at a younger firm age controlling for round stage, ranging from 348 days younger than their parent VC firm in specification (2-1) and 129 days younger in specification (4-1). They invest in founding teams that are statistically indistinguishable in size, which we made no prior prediction about. The individual partners invest in founding teams that are significantly younger, 1.07 years younger in specification (2-4) to .90 years younger in specification (2-5); we do not find a significant coefficient in (4-2). The founders have less prior entrepreneurial experience, with .24 less firms founded that received venture investment in their history in specification (2-1); the results on entrepreneurial experience are robust across all specifications. Across the education metrics, the founding teams that the individual partners choose to invest in have less formal education: fewer founding teams have founders with graduate degrees, MBAs, PhDs, and training in engineering, although statistical significance varies across specifications. For example, the angel partners invest in founding teams that are 5.8 percentage points less likely to have any graduate degree in specification (2-13). We find no significant results on the analysis of graduation from elite ranked institutions. We find broad support for Hypothesis 1.

1.7.2 Hypothesis 2: Cost of Tacit Information Acquisition

Table 1.5 and Figure 1.4 show the results of our analysis of the effect of geographic distance on investment uptake between the partner and the firm, as a test of Hypothesis 2. Table 1.5 is estimated using the Geography Model. There is a stark non-linearity in the results. Up to about 1000km,[39] greater distance is associated with

[39] 1000 kilometers is about 621 miles. The distance between San Francisco, CA and Seattle, WA is 1095km (681 miles). The distance between Boston, MA and San Francisco, CA is 4350km (2703

a higher probability of the investment being taken by the partner than the firm. After 1000km, more distance has a statistically insignificant effect. While further work has to be done to explore the consequences of this, one possibility is related to the limits of forms of transportation. Up to 1000km, it is feasible that the partner would make a land-based trip via car or train to visit the potential investment, and as that distance increases and approaches 1000km, it is less likely that non-sourcing partners would come to visit that investment opportunity to acquire their own private signal. After 1000km, we would imagine that the partners would predominately fly to visit their investments, minimizing the cost in effort to acquire information. Moreover, beyond we might think that VC firms have a particular advantage over individual investors in structuring geographically disparate investments: for example, international investments face alternative legal and coordination barriers that the VC firm may have the resources to tackle.

——————Insert Table 1.5——————

——————Insert Figure 1.4——————

1.7.3 Hypothesis 3: Tacit Information

Table 1.6 and Figure 1.5 show the results of our analysis of VC experience, measured by a count of prior investments, in a particular business model, technology method, or technology platform as implemented by the startup, as a test of Hypothesis 3. Table 1.6 is estimated with the Category Model. Across all categorizations and specifications, the increased experience by the VC is associated with a greater likelihood that the investment would be picked up by the VC and not by the partner on her own. VCs with greater experience in a particular category likely have a more

miles).

informative private signal across the partners to understand a new investment in the same category since they have already done so before. Specification (6-1) includes the full sample of firms that were categorized. One concern with the first specification is that the firm might have a pre-specified investment thesis stated to the limited partner outside investors that is contractually or implicitly binding and limits the scope of investments able to be executed by the firm. Specification (6-2) only looks at investments for which the VC has any experience in the category, and thus it is within the scope of any possible investment thesis.

——————Insert Table 1.6——————

——————Insert Figure 1.5——————

1.7.4 Venture Financial Performance

As a matter of empirical interest, we present the results of the descriptive analysis of venture financial performance in Table 1.7 and Table 1.8 estimated with the Main Model and Matching Model respectively. We caution the reader to not over interpret these results as causal, as there are a number of endogeneity issues that we have not controlled for: for example, we would expect the venture capital firm and the individual partner to have different capacities to add value to the entrepreneurial ventures. Nevertheless, we find inconclusive results regarding the financial performance differences. In all specifications about future funding rounds (7-1 through 7-6, 8-1 through 8-2), we do not find evidence of statistically significant difference. In specifications (7-7) through (7-9), investments backed by the angel partner are around 3 percentage points more likely to reach an acquisition exit, but this effect does not appear in the matching model (8-3). In the main model, they are around .5 percentage points less likely to reach an IPO exit in specifications 7-10 through 7-12), but this effect does not appear in the matching model (8-4). It is difficult to directly compare the aggregate financial value of the acquisitions and IPOs together, and the limited data available on the exit valuations[40] creates some doubt around the specifications (7-16) through (7-18) and (8-6).

We caution the reader into not over-interpreting the outcome variables in our analysis of venture financial performance. We don't observe the level to which the investor can add value to the investment ex-post (Hsu, 2004; Sørensen, 2007), constituting a substantive omitted variable. It is plausible the individual angel investors may add a different amount of value to their investments than the VC organizations, many of whom have formal structures for helping their startups. Our prior is that the venture capital firm should have more capacity to advise and monitor the investment since many VC firms maintain a number of resources, including formal contact lists (the "Rolodex"), executive and technology recruiting staff, legal support, as well as known reputations that signal the quality of the venture. For example, First Round Capital, based in Philadelphia, maintains an internal database of advisers and potential executive and technical hires for use by its portfolio companies. However, we posit that the individual partners of the venture capital firm would have access to many of the same resources that the firm itself would have, because they are employed by the venture capital firm and familiar with its resources. We cannot make any very generalizable conclusions about the financial performance differences between individual vs. VC investments. However, if the venture capital investments do not clearly outperform the angel partner investments, then on the assumption that the VC organization has more ability to add value to the investment and an individual angel partner, then we would suspect that the angel partner investments reflect compositionally ex ante

[40] There are small sample sizes on the exit valuation, because most M&A transactions do not disclose it and M&A transactions are by far the most common exit outcome.

stronger investments in the presence of analysis suggesting they are similar. However, there is limited theory to support this suspicion.

Insert Table 1.7

Insert Table 1.8

1.8 Conclusion

We study the role of information in organizational decision making for financing of entrepreneurial ventures. We formally model an organization of one or more agents who must make a dichotomous choice about whether or not to allocate resources to a particular project with an unknown outcome. The agents vote strategically and decide whether to acquire costly external information to improve their decision quality. We test our theoretical predictions in the setting of venture capital partnerships, where venture capital partners invest on their own outside of their employing firms. We find that the venture capital partners, acting independently, exhibit a number of different investment behaviors than their employing venture capital firm. They make investments into younger firms with less educated and younger founding teams, but these investments perform better on some metrics (future funding rounds, exit events) even when controlling for investment size and stage.

Our findings link to the broader literature of organization design, especially the core concepts of *incentive alignment* (e.g. Jensen and Meckling, 1976) and the *provision of information* (e.g. Schelling, 1980). In particular, it contributes to a growing literature on committee decision-making and information aggregation, which has long been overlooked by the organization design literature Csaszar and Eggers (2013), despite being one of the original but "forgotten pillars" (Gavetti et al., 2007) of the Carnegie tradition (Cyert and March, 1963). In a notable related work, Csaszar (2012) tests the predictions of the Sah and Stiglitz (1991) model of committee decision-making in a related setting, mutual fund managers, and he finds the organizational structure has significant effects on the rate of omission and commission errors in the setting of mutual fund stock picking.

Beyond decision-making and information, our work also fits thematically into the discussion on resource allocation in organizations. Leaders of organizations, whether they be a singular manager or a team of managers, must allocate resources to the most productive activities to maximize organizational performance (Baldwin and Clark, 1994; Bower, 1986; Cyert and March, 1963). This complex process involves the division, allocation, incentive alignment, and knowledge questions core to organizational design. An organization with a singular manager allocating resources can be thought of as *centralized*, while an organization with managers jointly allocating resources can be thought of as *decentralized* (Sah and Stiglitz, 1991). The venture capital partnership engages in a centralized decision-making process, while the angel partners acting independently could be thought of as engaging in a decentralized form of decision-making. The design choice between centralized and decentralized structures has tradeoffs for the organizations productivity, because they lead to different choices of resource allocation and thus different aggregate organizational performance.

Our theoretical model and empirical strategy can also lend itself to addressing the phenomenon of spin-outs, entrepreneurial ventures of ex-employees of large firms. There are competing theories explaining their origins. On one hand, agency models suggest an intrinsic conflict of interest between the employees and the firm as valuable discoveries arise that can be brought to market (e.g. Wiggins, 1995; Anton and Yao, 1995). On the other hand, incumbent firms may lack the organizational capabilities to recognize and take advantage of new opportunities (e.g. Christensen, 1993). Applying our findings to the setting of spin-outs, our work suggests that spin-outs can emerge even when incentives are aligned between the employee and the firm, as a consequence of the organizational form limiting access to information in the incumbent firm. In more recent work, Agarwal et al. (2004) find that spin-outs occur when incumbent firms lack both technological and market know-how. In other words, the organization is not structured to take advantage of new opportunities sourced by its employees. The resource allocation process may be set up such that the firm leaders lack the information or decision-making structure to recognize the opportunities in the first place. Any hierarchy involving teams must ultimately involve a decision-making process, leading to the age-old tension between individual vs. group decision-making which we study in a very specific setting.

There are several opportunities for research beyond present study. First, we do not have information on the exact voting behavior of the participants, a traditional advantage of lab experiments. Future work should use real life voting data, which we would like to see particularly in the venture capital setting. Second, we do not observe the risk set of investments rejected by both the venture capital firm and its angel partners, which could introduce some bias to the empirical estimates. Third, there are a number of other theoretical models that could explain a similar pattern of results. For example, the results could also be explained by heterogeneous utility function or heterogeneous signal quality (skill) across different participants. We do not strictly rule out other models, but the information based model we propose represents a parsimonious case that still explains our full slate of results.

Future work should consider the role of organizational decision-making and resource allocation in a variety of organizational forms. A simple extension would be to general private equity or hedge funds. In our model, we made the simplifying assumption that the agents made a dichotomous decision to invest or not. In the hedge fund industry, it is almost certainly a portfolio decision, so the model would have to be quite different. In addition, we are currently exploring other aspects of the implications of the partnership structure in venture capital firms. In particular, the substantial heterogeneity in voting mechanisms, hierarchical systems, and compensation structures used by venture capital partnerships merits additional exploration.

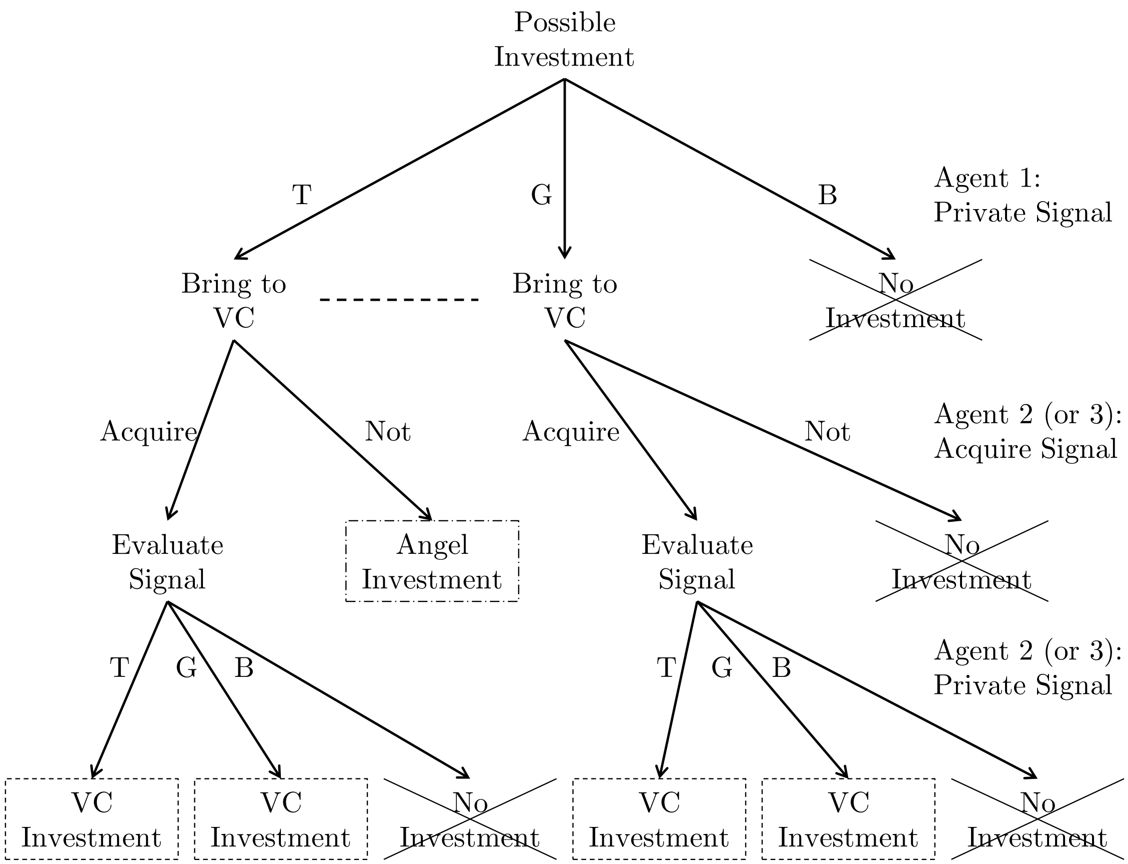

Figure 1.1: **Extensive Form Game**. This figure is the extensive form representation of the model in Section 1.2. T (terrific), G (good), B (bad) represent the information content of the private signal known to the respective agent but not directly known to the other agents. The dashed line shows that the other agents would not be able to distinguish between whether Agent 1 had a T or G private signal. *Angel Investment* means that the agent would take the investment herself. *VC Investment* means the investment is retained by the firm. *No Investment* means both the VC firm and the individual agent reject the investment. For the case of Agent 1 receiving a private signal T, Agent 2 acquiring the signal, and then Agent 2 receiving a private signal B, we make the optional assumption that $E[U|\sigma_i = T, \sigma_j = B] < 0$, resulting in no investment.

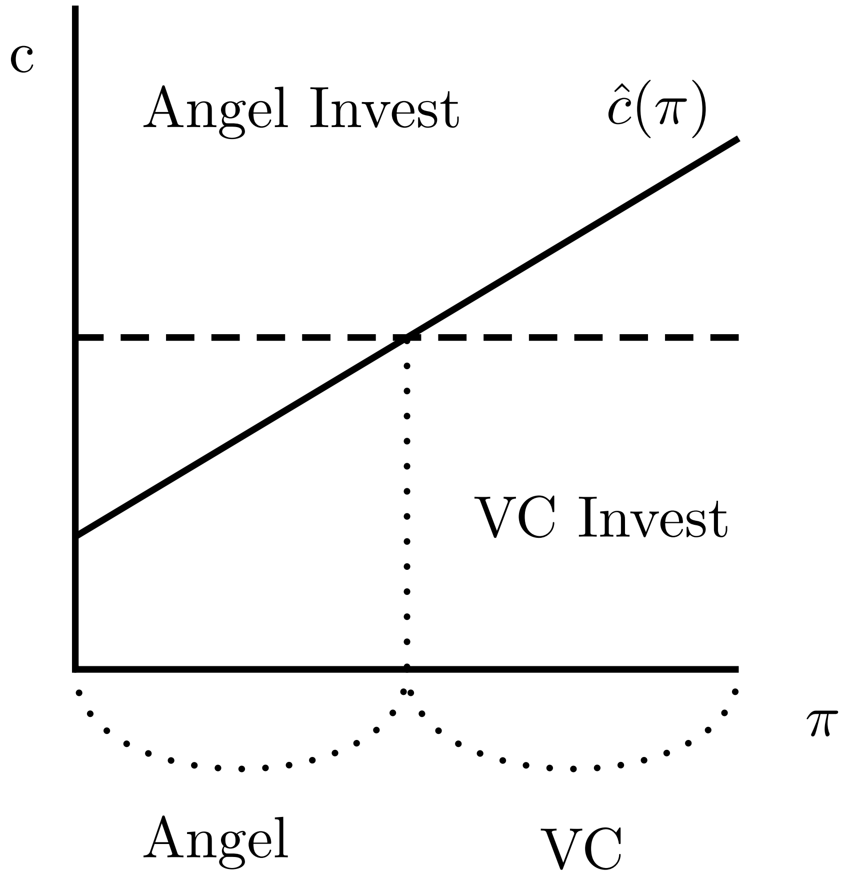

Figure 1.2: **VC vs. Angel Investment as Function of the Public Signal and Cost of Information**. This figure presents the implication of public signal π and information cost c on the investment vehicle outcome for the model in Section 1.2. π presents the information content of the public signal, c represents the cost of information acquisition, and $\widehat{c}(\pi)$ represents the threshold cost function for an agent to acquire the private signal. An investment with π and c placing it above the solid line representing $\widehat{c}(\pi)$ would be taken up by the individual angel investor if she has a private signal of T, and if it is below the line then it would be taken up by the VC if another agent has a favorable signal G or T. The horizontal dotted line shows the outcomes for a given level of c.

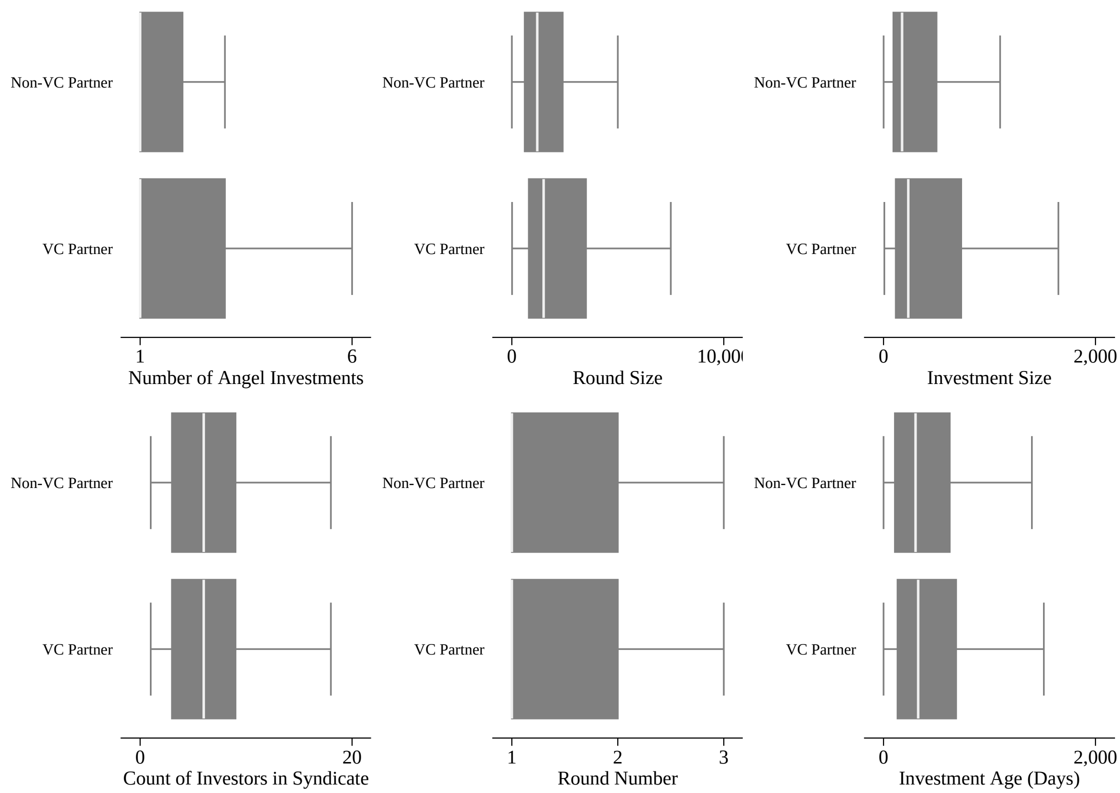

Figure 1.3: **VC Partner vs. Non-VC Affiliated Angels**. These box plots illustrate the compositional differences between angels who are full-time venture capital partners and angels who are not (e.g. former entrepreneurs, executives, etc.). The box itself represents the 25^{th} and 75^{th} percentile, the white line in the box represents the median, and the adjacent lines represent the bounds given by $\frac{3}{2}$ times the inter-quartile range. Outliners beyond the adjacent lines were omitted from the graph for presentational purposes. *Round Size* and *Investment Size* are in units of thousands of dollars USD. The *Investment Size* was imputed dividing the total size of the investment round for which an angel participated in, divided by the number of investors in the syndicate. Only *Number of Angel Investments*, *Round Size*, and *Investment Size* have a statistically significant difference (at beyond the 0.1% level) and the others do not have a significant difference. Source: Crunchbase 2005 to 2013.

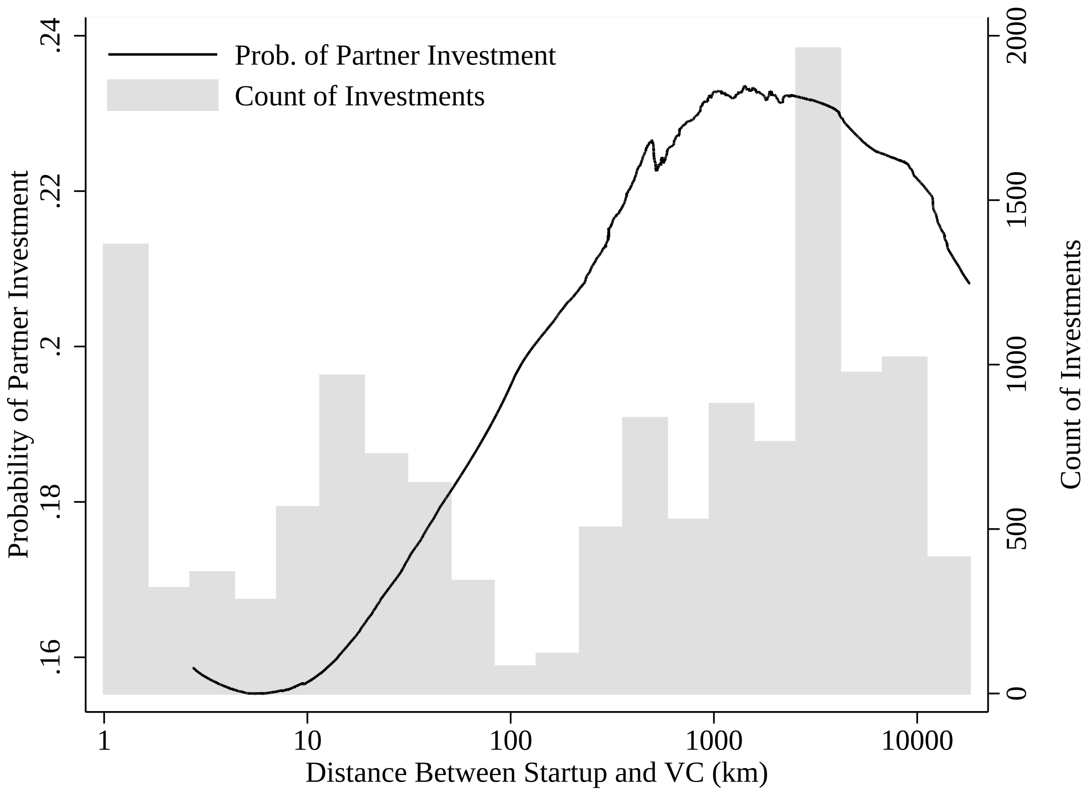

Figure 1.4: **Geographic Distance Between Venture and VC Offices**. This figure presents the relationship between geographic distance between the new venture and the offices of the venture capitalist and the investment vehicle outcome, in support of Hypothesis 2. The X-axis represents geodesic distance in kilometers between the main office of a startup and the closest office of the the VC making the investment or the employing VC of the angel partner who made the investment. Note that the X-axis is presented in a logarithmic scale. The left Y-axis and black line represents the probability that the investment is taken by an angel partner and not the employing VC. The right Y-axis and grey area represent a frequency histogram of investments at each distance. The figure was constructed with local linear smoothing (Cleveland, 1979). Source: Crunchbase 2005 to 2013.

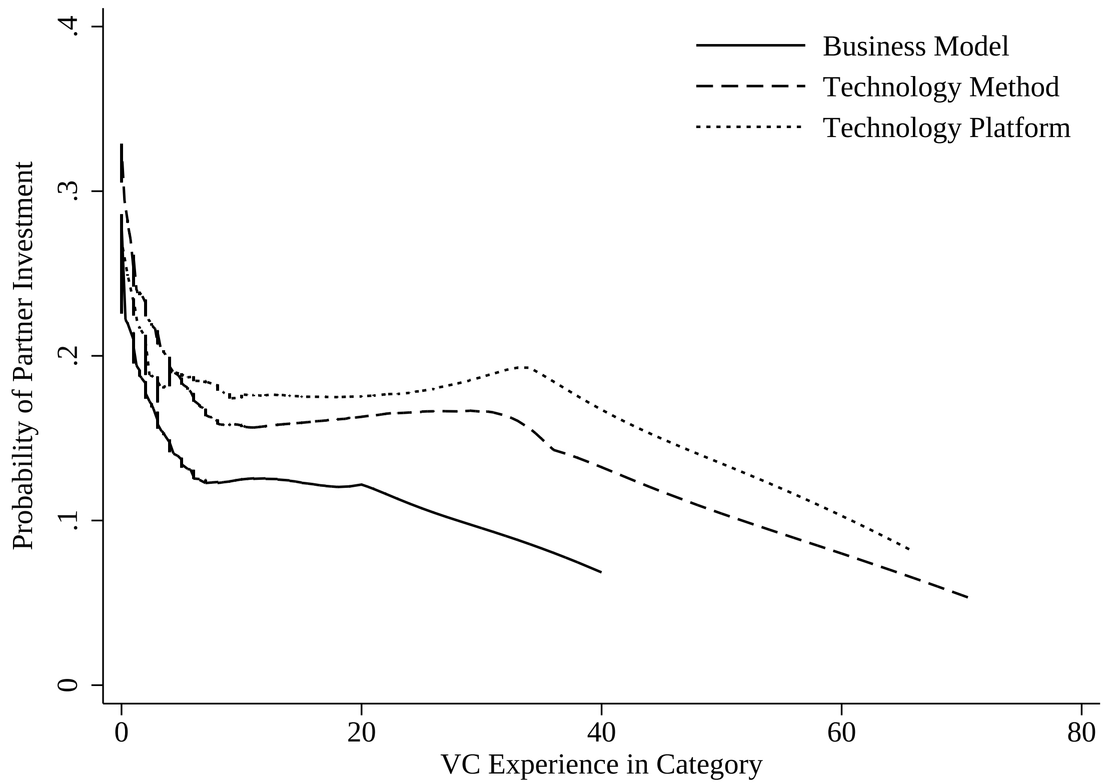

Figure 1.5: **VC Experience in Category**. This figure presents the relationship between a venture capital firm's experience in a category and the investment vehicle outcome, in support of Hypothesis 3. The X-axis represents the number of investments executed by the VC or the VC who employs the angel partner prior to the date of the investment in a given *Business Model*, *Technology Method*, or *Technology Platform* category. The Y-axis represents the probability that the investment is taken by an angel partner and not the employing VC. The figure was constructed with local linear smoothing (Cleveland, 1979). Source: Crunchbase 2005 to 2013.

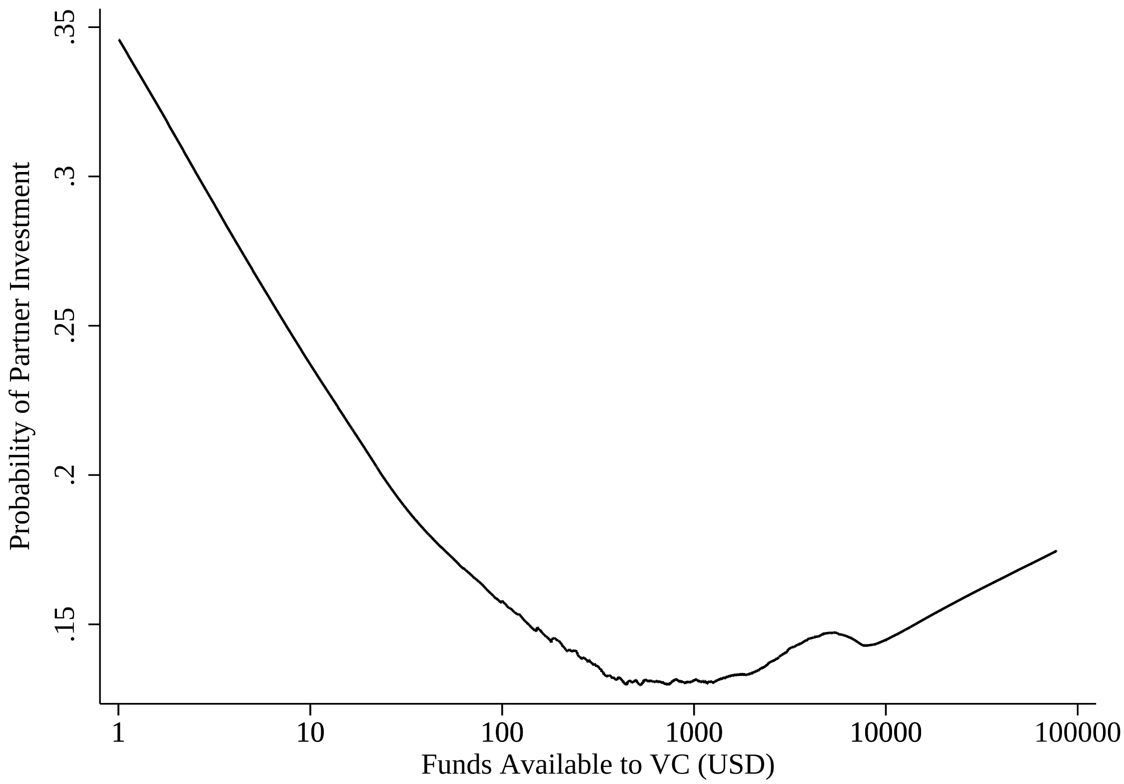

Figure 1.6: **VC Fund Availability**. The X-axis represents the imputed value of available limited partner (LP) funds to the VC firm, at the time of the investment: starting from the fund vintage year, where we assign the full value of the size of the fund, we discount the value of the fund by 10% of the starting value until it is fully exhausted in 10 years, summed across multiple funds. Note that the X-axis is presented in a logarithmic scale. The Y-axis represents the probability that the investment is taken by an angel partner and not the employing VC. The figure was constructed with local linear smoothing (Cleveland, 1979). Source: Crunchbase 2005 to 2013 and ThomsonOne VentureXpert.

Table 1.1: **Summary Statistics**. Summary statistics are presented for the partner angel investments and VC firm investments composing the full sample. Section 1 is the dependent variables for observable venture characteristics. Section 2 is the dependent variables for venture financial performance. Section 3 is the control variables. Section 4 the is the industry composition of the sample. Section 5 is the independent variables used to measure geographic distance and category experience.

	Partner Angel Investments		VC Firm Investments		Full Sample		
	Mean	**Std. Dev.**	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Age at Funding Round (in Days)	569.35	2302.72	1192.96	1920.45	0	62212	15766
Size of Founding Team	2.70	1.54	2.63	1.70	1	18	13254
Average Age of Founders	33.25	7.38	35.86	8.32	20	75	6583
Max Prior Number of Firms Founded	0.94	1.45	1.13	1.57	0	14	7754
At Least One Founder with Graduate Degree	0.61	0.49	0.66	0.47	0	1	8487
At Least One Founder with MBA	0.38	0.48	0.41	0.49	0	1	8487
At Least One Founder with Ph.D.	0.08	0.26	0.11	0.31	0	1	8487
At Least One Founder with Elite Institution	0.59	0.49	0.59	0.49	0	1	8487
At Least One Founder with Engineering	0.18	0.38	0.22	0.42	0	1	8487
Future Funding Round	0.48	0.50	0.48	0.50	0	1	18227
Number of Future Funding Rounds	0.85	1.17	0.87	1.22	0	9	18227
Acquisition Exit	0.21	0.41	0.18	0.38	0	1	18227
Exit (IPO/M&A)	0.22	0.41	0.20	0.40	0	1	18227
Exit Valuation (MM USD)	657	6,086	1,505	10,210	0	104,200	1360
IPO Exit	0.00	0.07	0.02	0.13	0	1	18227
Round Size (MM USD)	4.04	13.70	13.17	35.55	0.01	1500	16467
Syndicate Size	6.84	4.95	3.91	3.06	1	27	18073
Round Number	1.40	0.74	1.53	0.95	1	11	18227
Round Year	2010.08	2.10	2009.40	2.49	2005	2013	20993
Agriculture, Forestry, etc. (NAICS 11)	0.00	0.06	0.00	0.04	0	1	17410
Utilities (NAICS 22)	0.00	0.00	0.00	0.02	0	1	17410
Construction (NAICS 23)	0.01	0.09	0.03	0.18	0	1	17410
Manufacturing (NAICS 31)	0.00	0.02	0.00	0.01	0	1	17410
Manufacturing (NAICS 32)	0.00	0.07	0.00	0.06	0	1	17410
Manufacturing (NAICS 33)	0.06	0.24	0.15	0.35	0	1	17410
Wholesale Trade (NAICS 42)	0.01	0.09	0.00	0.06	0	1	17410
Retail Trade (NAICS 45)	0.05	0.22	0.05	0.22	0	1	17410
Transportation and Warehousing (NAICS 48)	0.00	0.02	0.00	0.02	0	1	17410
Transportation and Warehousing (NAICS 49)	0.00	0.00	0.00	0.04	0	1	17410
Information (NAICS 51)	0.44	0.50	0.36	0.48	0	1	17410
Finance and Insurance (NAICS 52)	0.04	0.20	0.03	0.18	0	1	17410
Real Estate (NAICS 53)	0.00	0.07	0.00	0.06	0	1	17410
Prof., Sci., Tech. Services (NAICS 54)	0.23	0.42	0.24	0.43	0	1	17410
Administrative and Support (NAICS 56)	0.02	0.15	0.01	0.11	0	1	17410
Educational Services (NAICS 61)	0.03	0.16	0.02	0.14	0	1	17410
Health Care & Social Assistance (NAICS 62)	0.01	0.11	0.02	0.16	0	1	17410
Arts, Entertainment & Recreation (NAICS 71)	0.02	0.16	0.01	0.12	0	1	17410
Accommodation & Food Services (NAICS 72)	0.01	0.08	0.00	0.04	0	1	17410
Other Services (NAICS 81)	0.00	0.06	0.00	0.04	0	1	17410
Public Administration (NAICS 92)	0.00	0.05	0.00	0.04	0	1	17410
Distance (km)	2344.34	3231.57	2196.08	3208.96	0	18106.05	13662
VC Exp. in Business Model	0.32	1.76	0.79	2.86	0	40	17318
VC Exp. in Technology Method	1.31	3.61	2.41	4.94	0	71	17318
VC Exp. in Technology Platform	1.03	3.74	1.68	5.01	0	66	17318
Observations	5107		15897				

Table 1.2: **Main Model: Venture Characteristics**. This table presents a descriptive multivariate analysis for Hypothesis 1 with various dependent variables for favorable observable venture characteristics. The first two models for each dependent variable are estimated with the full sample, and the third is estimated with the sub-sample of the first and second rounds of investment. The Main Model is estimated with OLS. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors clustered at the organizational level are shown in parentheses.

	Firm Age			**Founder Age**			**Team Size**		
	(2-1)	(2-2)	(2-3)	(2-4)	(2-5)	(2-6)	(2-7)	(2-8)	(2-9)
Angel Investor	-347.776***	-279.923***	-228.309***	-1.072***	-0.900***	-0.980***	-0.048	-0.076	-0.056
	(70.27)	(74.49)	(83.75)	(0.29)	(0.29)	(0.32)	(0.05)	(0.05)	(0.05)
Round Size	4.562***	4.033***	15.426***	0.047***	0.043***	0.070***	-0.002***	-0.001***	-0.002
	(1.08)	(1.01)	(1.99)	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Syndicate Size	-3.332	-4.968	-3.027	-0.241***	-0.218***	-0.207***	0.028***	0.029***	0.032***
	(4.80)	(4.81)	(5.11)	(0.03)	(0.03)	(0.03)	(0.00)	(0.00)	(0.01)
Observations	14179	13129	11310	5195	4879	4137	10332	9708	8311
	Prior Entrepreneurial Exp.			**Education: Graduate Degree**			**Education: MBA**		
	(2-10)	(2-11)	(2-12)	(2-13)	(2-14)	(2-15)	(2-16)	(2-17)	(2-18)
Angel Investor	-0.235**	-0.246**	-0.192*	-0.058***	-0.058***	-0.027	-0.029*	-0.021	0.00
	(0.10)	(0.10)	(0.11)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Round Size	-0.001*	0.00	0.004**	0.00	0.00	0.002***	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate Size	0.016*	0.020**	0.016*	-0.002	-0.001	-0.002	0.005***	0.005***	0.003*
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6147	5807	4844	6688	6305	5315	6688	6305	5315
	Education: PhD			**Education: Elite Institution**			**Education: Engineering**		
	(2-19)	(2-20)	(2-21)	(2-22)	(2-23)	(2-24)	(2-25)	(2-26)	(2-27)
Angel Investor	-0.034***	-0.030***	-0.019*	0.007	0.001	-0.01	-0.040**	-0.032**	-0.027
	(0.01)	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Round Size	0.00	0.00	0.002***	-0.000*	0.00	0.001	0.00	0.00	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate Size	-0.002**	-0.002*	-0.001	0.001	0.003	0.002	0.001	0.001	0.001
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	6688	6305	5315	6688	6305	5315	6688	6305	5315
Sample	Full	Full	Rnd 1&2	Full	Full	Rnd 1&2	Full	Full	Rnd 1&2
Org. FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes

Table 1.3: **Summary Statistics: Matching Model**. This table presents the data used for the Matching Model. Starting with the full sample of angel partner investments, we match each angel investment with the venture capital investment that is in the same 2 digit NAICS class and closest in total round size and then round date, with a maximum of $1 million different in round size. We drop angel investments that do not have a match.

	Partner Angel Investment		**VC Firm Investment**	
	Mean	**SD**	**Mean**	**SD**
Age at Funding Round (in Days)	510.58	1943.77	678.93	1564.45
Size of Founding Team	2.71	1.47	2.75	1.61
Average Age of Founders	33.40	7.29	33.16	7.65
Max Prior Number of Firms Founded	0.94	1.30	1.01	1.49
At Least One Founder with Graduate Degree	0.58	0.49	0.62	0.49
At Least One Founder with MBA	0.37	0.48	0.39	0.49
At Least One Founder with Ph.D.	0.07	0.25	0.08	0.27
At Least One Founder with Elite Institution	0.59	0.49	0.63	0.48
At Least One Founder with Engineering	0.17	0.38	0.20	0.40
Future Funding Round	0.48	0.50	0.45	0.50
Number of Future Funding Rounds	0.83	1.11	0.73	1.06
Acquisition Exit	0.20	0.40	0.17	0.37
Exit (IPO/M&A)	0.20	0.40	0.17	0.38
Exit Valuation (MM USD)	393.22	1757.44	137.03	228.27
IPO Exit	0.00	0.05	0.00	0.05
Round Size (MM USD)	2.41	3.61	2.43	3.59
Syndicate Size	7.29	4.95	4.67	3.86
Round Number	1.41	0.74	1.43	0.70
Round Year	2009.89	1.94	2010.00	1.98
Observations	2458		2458	

Table 1.4: **Matching Model: Venture Characteristics**. This table presents the results of the Matching Model analysis for Hypothesis 1 with various dependent variables for favorable observable venture characteristics. The Matching Model is estimated with OLS. Statistical significance is represented by $* p < 0.10$, $** p < 0.05$, and $*** p < 0.01$. Robust standard errors are shown in parentheses.

	Firm	**Founder**	**Team**	**Prior**	**Education:**				
	Age	**Age**	**Size**	**Entrep.**	**Graduate**	**MBA**	**PhD**	**Elite**	**Eng.**
	(4-1)	(4-2)	(4-3)	(4-4)	(4-5)	(4-6)	(4-7)	(4-8)	(4-9)
Angel Investor	-128.659**	0.279	-0.122**	-0.200*	-0.043**	-0.034*	-0.017	-0.032	-0.050***
	(56.65)	(0.34)	(0.05)	(0.10)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Round Size	110.311***	0.336***	0.042***	0.065***	0.015***	0.011***	0.001	0.012***	0.004
	(8.71)	(0.05)	(0.01)	(0.02)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate Size	-12.629*	-0.265***	0.042***	0.029**	-0.004*	-0.002	-0.001	0.003	0.005***
	(6.67)	(0.04)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Organization FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4298	2065	3735	2332	2538	2538	2538	2538	2538

Table 1.5: **Geography Model**. This table presents the results of the Geography Model analysis for Hypothesis 2. The Geography Model is estimated with OLS. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors are shown in parentheses.

	Angel Investor
	(5-1)
L Distance	0.002
	(0.005)
Distance (100 to 1000km)	-0.172**
	(0.084)
L Distance × Distance (100 to 1000km)	0.028*
	(0.014)
Distance (1000 to 10000km)	-0.011
	(0.085)
L Distance × Distance (1000 to 10000km)	0.001
	(0.011)
Distance (10000 to 100000km)	1.843
	(1.419)
L Distance × Distance (10000 to 100000km)	-0.196
	(0.150)
Round Size	-0.001***
	(0.000)
Syndicate Size	0.028***
	(0.002)
Organization FE	Yes
Year FE	Yes
Round FE	Yes
Industry FE	Yes
Observations	11719

Table 1.6: **Category Experience Model**. This table presents the results of the Category Model analysis for Hypothesis 3. The *Full* sample contains all firms for which we were able to categorize. One concern with the first specification is that the firm might have a pre-specified investment thesis stated to the limited partner outside investors that is contractually or implicitly binding and limits the scope of investments able to be executed by the firm. The *Experience* sample limits the angel investments to those contain for which the VC has any experience in the category, and thus it is within the scope of any possible investment thesis. The Category Model is estimated with OLS. Statistical significance is represented by $*\, p < 0.10$, $**\, p < 0.05$, and $***\, p < 0.01$. Robust standard errors are shown in parentheses.

	Angel Investor	
	(6-1)	**(6-2)**
VC Exp. in Business Model	-0.008***	-0.007***
	(0.00)	(0.00)
VC Exp. in Technology Method	-0.008***	-0.007***
	(0.00)	(0.00)
VC Exp. in Technology Platform	-0.004***	-0.004***
	(0.00)	(0.00)
Round Size	-0.001***	-0.001***
	(0.00)	(0.00)
Syndicate Size	0.026***	0.027***
	(0.00)	(0.00)
Sample	Full	Experience
Organization FE	Yes	Yes
Year FE	Yes	Yes
Round FE	Yes	Yes
Observations	10620	9201

Table 1.7: **Main Model: Venture Financial Performance**. This table presents the results of the analysis of financial performance with various dependent variables for venture financial performance. The Main Model is estimated with OLS. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors clustered at the organizational level are shown in parentheses.

	Future Funding Round			**Number of Future Rounds**		
	(7-1)	(7-2)	(7-3)	(7-4)	(7-5)	(7-6)
Angel Investor	0.011	-0.007	-0.005	0.043	0.005	0.003
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Round Size	0.00	0.00	-0.001***	0.00	0.00	-0.003***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate Size	0.005***	0.006***	0.006***	0.008**	0.010***	0.010***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	16339	15059	13174	16339	15059	13174

	Acquisition Exit			**IPO Exit**		
	(7-7)	(7-8)	(7-9)	(7-10)	(7-11)	(7-12)
Angel Investor	0.038***	0.031***	0.028**	-0.004*	-0.005**	-0.005**
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)	(0.00)
Round Size	0.000**	0.000***	0.00	0.001***	0.001***	0.001***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Syndicate Size	0.006***	0.006***	0.006***	0.001	0.001*	0.001**
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
Observations	16339	15059	13174	16339	15059	13174

	Exit (IPO/M&A)			**Exit Valuation**		
	(7-13)	(7-14)	(7-15)	(7-16)	(7-17)	(7-18)
Angel Investor	0.030***	0.023**	0.022**	-657.098	-236.653	-77.885
	(0.01)	(0.01)	(0.01)	(552)	(278)	(69)
Round Size	0.001***	0.001***	0.001**	12.307***	11.764***	-3.242
	(0.00)	(0.00)	(0.00)	(1.75)	(1.10)	(3.68)
Syndicate Size	0.007***	0.007***	0.007***	-35.40	29.18	2.84
	(0.00)	(0.00)	(0.00)	(39.23)	(38.12)	(20.34)
Observations	16339	15059	13174	1229	1150	943

Sample	Full	Full	Rnd. 1 & 2	Full	Full	Rnd. 1 & 2
Org. FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	Yes	Yes	No	Yes	Yes

Table 1.8: **Matching Model: Venture Financial Performance**. This table presents the results of the Matching Model analysis of financial performance with various dependent variables for venture financial performance. The Matching Model is estimated with OLS. Statistical significance is represented by $*\,p < 0.10$, $**\,p < 0.05$, and $***\,p < 0.01$. Robust standard errors are shown in parentheses.

	Future Round	**# Future Rounds**	**Acq. Exit**	**IPO Exit**	**Exit**	**Exit Valuation**
	(8-1)	(8-2)	(8-3)	(8-4)	(8-5)	(8-6)
Angel Investor	-0.008	0.024	0.004	0.000	0.003	44.76
	(0.01)	(0.03)	(0.01)	(0.00)	(0.01)	(39.96)
Round Size	-0.004**	-0.001	0.001	0.001***	0.001	16.327***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(2.93)
Syndicate Size	0.009***	0.016***	0.006***	0.00	0.007***	-20.096***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(6.01)
Organization FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Round FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4862	4862	4862	4862	4862	287

Table 1.9: **Fund Availability Model**. This tables presents the results of the analysis of VC fund access. The model is estimated with OLS. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors clustered at the organizational level are shown in parentheses.

	Angel Investor
	(8-1)
L Funds Available	-0.018
	(0.01)
Round Size	-0.001***
	(0.00)
Syndicate Size	0.030***
	(0.00)
Organization FE	Yes
Year FE	Yes
Round FE	Yes
Industry FE	Yes
Observations	10359

Table 1.10: **Missing Data**. This table presents the correlations between an indicator for missing founding team data and various variables that we have for the full sample.

Correlation with Missing Data Indicator	
Angel Investor	-0.20
Age at Funding Round (in Days)	0.15
Future Funding Round	-0.09
Number of Future Funding Rounds	-0.09
Acquisition Exit	-0.03
Exit (IPO/M&A)	-0.03
Exit Valuation (IPO/M&A)	-0.07
IPO Exit	0.00
Funding Round Amount	0.06
Count of Investors in Syndicate	-0.19
Round Number	-0.12
Round Year	-0.16

1.A Appendix: Stylized Model

1.A.1 Parameter Restrictions

Assumption 2 and Assumption 3 are satisfied automatically from the original assumptions.[41]

$$\underbrace{E[U|\sigma = B] < E[U]}_{\text{Assumption 2}} \Leftrightarrow q > \frac{1}{2}$$

$$\underbrace{E[U|\sigma = G] > E[U]}_{\text{Assumption 3}} \Leftrightarrow q(1-\theta) > (1-q)(1-\beta)$$

$$\Leftrightarrow \frac{1-q}{q} < \frac{1-\theta}{1-\beta}$$

Assumption 4, Assumption 6, and Assumption 6b hold if and only if the following conditions are met[42]:

$$\underbrace{E[U|\sigma = T] > 0}_{\text{Assumption 4}} \Leftrightarrow \pi q \theta U(1) + (1-\pi)(1-q)\beta U(0) > 0$$

$$\Leftrightarrow \frac{1-q}{q} < \left(\frac{\theta}{\beta}\right)\left(\frac{\pi}{1-\pi}\right)\left(-\frac{U(1)}{U(0)}\right)$$

$$\underbrace{E[U|\sigma \in \{G,T\}] < 0}_{\text{Assumption 5}} \Leftrightarrow \pi q U(1) + (1-\pi)(1-q)U(0) < 0$$

$$\Leftrightarrow \frac{1-q}{q} > \left(\frac{\pi}{1-\pi}\right)\left(-\frac{U(1)}{U(0)}\right)$$

$$\underbrace{E[U|\sigma_i = G, \sigma_j = G] > 0}_{\text{Assumption 6b}} \Leftrightarrow \pi q^2(1-\theta)^2 U(1) + (1-\pi)(1-q)^2(1-\beta)^2 U(0) > 0$$

$$\Leftrightarrow \frac{1-q}{q} < \sqrt{\left(\frac{\pi}{1-\pi}\right)\left(-\frac{U(1)}{U(0)}\right)}$$

[41] Assumption 3 holds as long as θ is not that much larger than β, given $q \in (\frac{1}{2}, 1)$.

[42] Assumption 4 is sure to be satisfied as $\theta/\beta \to +\infty$. When θ/β is large, the terrific signal, $\sigma = T$, is far more likely for the profitable state ($s = 1$) than for the unprofitable state ($s = 0$), conditional on receiving a favorable signal (i.e., $\sigma \in \{G, T\}$).

Given Assumption 5, the original parameter restrictions imply Assumption 1 and Assumption 6a.

$$\underbrace{E[U|\sigma \in \{G,T\}] < 0}_{\text{Assumption 5}} \Rightarrow \underbrace{E[U|\sigma = G] < 0}_{\text{Assumption 6a}} \Rightarrow \underbrace{E[U] < 0}_{\text{Assumption 1}} .$$

Assumptions 1 through 6 are sufficient to characterize the equilibrium. We can further add an additional assumption for $E[U|\sigma_i = T, \sigma_j = B]$ to cover all cases of voting by the organization. This case would represent the scenario where agent 1 receives a signal of $\sigma_1 = T$ and agent 2 acquires signal but receives $\sigma_2 = B$. We assume that agent 1 would not pursue the deal on her own, but this assumption is not necessary for the model or its empirical predictions.

$$\begin{aligned}
E[U|\sigma_i = T, \sigma_j = B] < 0 &\Leftrightarrow \frac{\pi q \theta (1-q) U(1) + (1-\pi)(1-q)}{\pi\theta(1-q) + (1-\pi)(1-q)\beta q} < 0 \\
&\Leftrightarrow \left(\frac{\pi}{1-\pi}\right)\left(-\frac{U(1)}{U(0)}\right) < \frac{\beta}{\theta} \\
&\Leftrightarrow \phi_\pi \phi_U < \frac{\beta}{\theta}
\end{aligned}$$

1.A.2 No Equilibrium with Both Agents Acquiring a Signal

If agent 3 does not acquire a signal, given her current expectation $E[U|\sigma_1 \in \{G,T\}] < 0$, then she will vote against the project, giving her expected utility of

$$\begin{aligned}
&\underbrace{\Pr(\sigma_2 \in \{G,T\}\,|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}]}_{\text{Agent 2 Favorable Signal}} \\
&+ \underbrace{\Pr(\sigma_2 = B\,|\sigma_1 \in \{G,T\}) \times 0}_{\text{Agent 2 Unfavorable Signal}}.
\end{aligned}$$

If agent 3 instead acquires a signal, she will vote for the project when $\sigma_3 \in \{G,T\}$–in which case it will be funded as there will be at least two votes in support–and vote against it when $\sigma_3 = B$–in which case it will be funded if and only if $\sigma_2 \in \{G,T\}$. The associated expected utility to agent 3 (after netting out the cost of the signal) is:

$$\underbrace{\begin{bmatrix} \Pr(\sigma_2 \in \{G,T\}\,|\sigma_1 \in \{G,T\}\,) \\ \times E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}] \end{bmatrix}}_{\text{Agent 2 Favorable Signal}}$$

$$+ \underbrace{\begin{bmatrix} \Pr(\sigma_2 = B\,|\sigma_1 \in \{G,T\}\,)\Pr(\sigma_3 \in \{G,T\}\,|\sigma_1 \in \{G,T\}, \sigma_2 = B\,) \\ \times E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}] \end{bmatrix}}_{\text{Agent 2 Unfavorable Signal, Agent 3 Favorable Signal}}$$

$$+ \underbrace{[\Pr(\sigma_2 = B\,|\sigma_1 \in \{G,T\}\,)\Pr(\sigma_3 = B\,|\sigma_1 \in \{G,T\}, \sigma_2 = B\,) \times 0]}_{\text{Agents 2 \& 3 Unfavorable Signal}} - c$$

The expected utility of agent 3 acquiring the signal exceeds the expected utility of agent 3 not acquiring the signal when:

$$\Pr(\sigma_2 = B\,|\sigma_1 \in \{G,T\}\,)\Pr(\sigma_3 \in \{G,T\}\,|\sigma_1 \in \{G,T\}, \sigma_2 = B\,)$$
$$\times E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}] > c.$$

If this condition could be met, then agent 3 would acquire the signal. We will show that this condition cannot hold because $E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}] < 0$. When agent 3's vote is pivotal and she receives a favorable signal (and votes for it), the expected utility of funding the project is negative.

$$
\begin{aligned}
&E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}] \\
&= \Pr(s=1\,|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})U(1) \\
&\quad + \Pr(s=0\,|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})U(0).
\end{aligned}
$$

To solve for this, we solve to the probabilities in the expected utility expression. $\Pr(s=0\,|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})$ follows similarly.

$$
\begin{aligned}
&\Pr(s=1\,|\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}) \\
&= \frac{\Pr(s=1, \sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})}{\Pr(\sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})} \\
&= \frac{\Pr(s=1, \sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})}{\sum\limits_{s \in 0,1} \Pr(s, \sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\})}
\end{aligned}
$$

By the conditional independence of agents' signals,

$$
\begin{aligned}
&\Pr(s=1, \sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}) \\
&= \Pr(s=1)\Pr(\sigma_1 \in \{G,T\}\,|s=1)\Pr(\sigma_2 = B\,|s=1)\Pr(\sigma_3 \in \{G,T\}\,|s=1) \\
&= \pi q(1-q)q = \pi q^2(1-q) \\
&\Pr(s=0, \sigma_1 \in \{G,T\}, \sigma_2 = B, \sigma_3 \in \{G,T\}) \\
&= \Pr(s=0)\Pr(\sigma_1 \in \{G,T\}\,|s=0)\Pr(\sigma_2 = B\,|s=0)\Pr(\sigma_3 \in \{G,T\}\,|s=0) \\
&= (1-\pi)(1-q)q(1-q) = (1-\pi)q(1-q)^2
\end{aligned}
$$

Combining these expressions, we find an equivalence between the condition probability of the state with only one favorable signal and two favorable signals and an unfavorable signal.

$$
\begin{aligned}
&\Pr(s = 1\,|\sigma_1 \in \{G, T\}, \sigma_2 = B, \sigma_3 \in \{G, T\}\,) \\
&= \frac{\pi q^2(1-q)}{\pi q^2(1-q) + (1-\pi)q(1-q)^2} \\
&= \frac{\pi q}{\pi q + (1-\pi)(1-q)} \\
&= \Pr(s = 1\,|\sigma_1 \in \{G, T\}\,)
\end{aligned}
$$

$\Pr(s = 1\,|\sigma_1 \in \{G, T\}, \sigma_2 = B, \sigma_3 \in \{G, T\}\,) = \Pr(s = 1\,|\sigma_1 \in \{G, T\}\,)$ follows similarly.

Putting this back into our original expression for $E[U|\sigma_1 \in \{G, T\}, \sigma_2 = B, \sigma_3 \in \{G, T\}]$, we find

$$
E[U|\sigma_1 \in \{G, T\}, \sigma_2 = B, \sigma_3 \in \{G, T\}] = E[U|\sigma_1 \in \{G, T\}]
$$

which is assumed to be negative from Assumption 5.

Since $E[U(\sigma_1, \sigma_2, \sigma_3)|\sigma_1 \in \{G, T\}, \sigma_2 = B] < 0$, then the condition $E[U(\sigma_1, \sigma_2, \sigma_3)|\sigma_1 \in \{G, T\}, \sigma_2 = B] > 0$ cannot hold, which means it cannot be optimal for agent 3 to acquire a signal given agent 2 does acquire the signal. [43]

[43] The lack of an equilibrium with both agents 2 and 3 acquiring signals is predicated upon a voting rule in which an agent votes yes if and only if her signal is G or T. However, that voting rule need not be optimal when both agents acquire signals. This raises the question of whether an equilibrium exists in which both agents 2 and 3 acquire signals and agents vote yes if and only if her signal is T.

1.A.3 Equilibrium with One Agent or No Agents Acquiring a Signal

The acquisition of the signal is optimal if and only if

$$\Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}] \geq c$$

Expanding the left-hand side expression,

$$\begin{aligned}
&\Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\})E[U|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}] \\
=&\Pr(\sigma_2 \in \{G,T\}|\sigma_1 \in \{G,T\}) \\
&\times \left[\sum_{s\in 0,1} \Pr(s\,|\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\}\,)U(s)\right] \\
=&\left(\frac{\Pr(\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\})}{Pr(\sigma_1 \in \{G,T\})}\right) \\
&\times \left[\sum_{s\in 0,1} \left(\frac{\Pr(s, \sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\})}{\Pr(\sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\})}\right)U(s)\right] \\
=&\left(\frac{\Pr(s=1, \sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\})}{Pr(\sigma_1 \in \{G,T\})}\right)U(1) \\
&+\left(\frac{\Pr(s=0, \sigma_1 \in \{G,T\}, \sigma_2 \in \{G,T\})}{Pr(\sigma_1 \in \{G,T\})}\right)U(0)
\end{aligned}$$

The probabilities in the expression are

$$
\begin{aligned}
&\frac{\Pr(s=1,\sigma_1\in\{G,T\},\sigma_2\in\{G,T\})}{\Pr(\sigma_1\in\{G,T\})}\\
&=\frac{\Pr(s=1)\Pr(\sigma_1\in\{G,T\}\,|s=1)\Pr(\sigma_2\in\{G,T\}\,|s=1)}{\Pr(s=1)\Pr(\sigma_1\in\{G,T\}\,|s=1)+\Pr(s=0)\Pr(\sigma_1\in\{G,T\}\,|s=0)}\\
&=\frac{\pi q^2}{\pi q+(1-\pi)(1-q)}\\
&\frac{\Pr(s=0,\sigma_1\in\{G,T\},\sigma_2\in\{G,T\})}{Pr(\sigma_1\in\{G,T\})}\\
&=\frac{\Pr(s=0)\Pr(\sigma_1\in\{G,T\}\,|s=0)\Pr(\sigma_2\in\{G,T\}\,|s=0)}{\Pr(s=1)\Pr(\sigma_1\in\{G,T\}\,|s=1)+\Pr(s=0)\Pr(\sigma_1\in\{G,T\}\,|s=0)}\\
&=\frac{(1-\pi)(1-q)^2}{\pi q+(1-\pi)(1-q)}
\end{aligned}
$$

Hence,

$$\Pr(\sigma_2\in\{G,T\}|\sigma_1\in\{G,T\})E[U|\sigma_1\in\{G,T\},\sigma_2\in\{G,T\}]\geq c$$

$$\Leftrightarrow \widehat{c}\equiv\frac{\pi q^2U(1)+(1-\pi)(1-q)^2U(0)}{\pi q+(1-\pi)(1-q)}\geq c$$

1.A.4 Optimality of Voting Rule

We assumed that an agent's voting rule has her vote in support of the project if and only if:

1. she acquired a signal and the signal is favorable, $\sigma_i\in\{G,T\}$;

2. she did not acquire a signal and based on her current beliefs she expects the project to be profitable.

For the equilibria characterized above, we will now show that this voting rule is optimal and the agents vote sincerely (Austen-Smith and Banks, 1996; Persico, 2004).

Consider the equilibrium in which agents 2 and 3 do not acquire signals. As both of those agents will vote against the project, agent 1 is not pivotal in which case voting for the project (as prescribed by agent 1's voting rule) is trivially optimal. Turning to agent 2, she expects agent 1 to vote for the project and agent 3 to vote against it (because agent 2 expects agent 3 not to acquire a signal). As agent 2 is pivotal, the project is not funded if agent 2 votes against it, in which case her payoff is zero, and the project is funded if she votes for it and that yields expected utility of $E[U|\sigma_1 \in \{G,T\}]$ which is negative. Hence, it is optimal for agent 2 not to vote for the project. By symmetry, the same argument applies to agent 3. We conclude that the voting rule is optimal for the equilibrium in which agents 2 and 3 do not acquire signals.

Next consider the equilibrium in which agent 2 acquires a signals and agent 3 does not. Beginning with agent 1, he is pivotal if and only if agent 2 receives a favorable signal, $\sigma_2 \in \{G,T\}$, and thus votes in favor of funding to project and that offsets agent 3's vote in opposition. It is optimal for agent 1 to vote for the project when $\sigma_1 \in \{G,T\}$ if $E[U|\sigma_1, \sigma_2 \in \{G,T\}]$ for $\sigma_1 \in \{G,T\}$. This expected utility is assumed to be positive by Assumption 6 on the expected utility, and thus agent 1's voting rule is optimal. Given agent 1 is expected to vote for and agent 3 against, agent 2 is pivotal in which case voting for the project if and only if agent 2's signal is favorable is optimal when

$$E[U|\sigma_1 \in \{G,T\}, \sigma_2] > 0 > E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B],\ \sigma_2 \in \{G,T\}$$

or

$$E[U|\sigma_1 \in \{G,T\}, \sigma_2 = G] > 0 > E[U|\sigma_1 \in \{G,T\}, \sigma_2 = B].$$

This condition follow from prior assumptions that

$$E[U|\sigma_1 = G, \sigma_2 = G] > 0 > E[U|\sigma_1 \in \{G, T\}].$$

Agent 2's voting rule is then optimal. Finally, agent 3's vote is pivotal only when $\sigma_2 = B$ in which case the expected utility of the project is $E[U|\sigma_1 \in \{G, T\}, \sigma_2 = B] < 0$; given that it is negative, it is optimal for agent 3 to vote against it. We conclude that the symmetric voting rule forms an equilibrium.

1.A.5 Empirical Hypotheses

We explore the comparative statics of $\hat{c}$ with respect to π and q.

$$\begin{aligned}
\frac{d\widehat{c}}{d\pi} =&[\pi q(1-\pi)(1-q)][2\pi qU(1) - 2(1-\pi)(1-q)U(0)] \\
&- [\pi q^2U(1) + (1-\pi)(1-q)^2U(0)][\pi - 1 + \pi] \\
=&2\pi^2q^2U(1) - 2(1-\pi)(1-q)U(0)\pi q \\
&+ 2\pi(1-\pi)(1-q)qU(1) - 2(1-\pi)^2(1-q)^2U(0) \\
&+ \pi q^2U(1) + (1-\pi)(1-q)^2U(0) \\
&- 2\pi^2q^2U(1) - 2\pi(1-\pi)(1-q)^2U(0) \\
=&2\pi(1-\pi)(1-q)q(U(1) - U(0)) + \pi q^2U(1) \\
&+ (1-\pi)(1-q)^2U(0)[-2(1-\pi) + 1 - 2\pi] \\
=&2\pi(1-\pi)(1-q)q(U(1) - U(0)) + \pi q^2U(1) - (1-\pi)(1-q)^2U(0) > 0
\end{aligned}$$

$$\begin{aligned}
\frac{d\widehat{c}}{dq} =&[2\pi qu_1 - 2(1-\pi)(1-q)u_0][\pi q + (1-\pi)(1-q)] \\
&- [\pi q^2u_1 + (1-\pi)(1-q)2u_0](2\pi - 1) \\
=&2\pi^2q^2u_1 + 2\pi(1-\pi)q(1-q)u_1 - 2\pi(1-\pi)q(1-q)u_0 - 2(1-\pi)^2(1-q)^2u_0 \\
&- 2\pi^2q^2u_1 + \pi q^2u_1 - 2\pi(1-\pi)(1-q)^2u_0 + (1-\pi)(1-q)^2u_0 \\
=&2\pi(1-\pi)q(1-q)(u_1 - u_0) - 2(1-\pi)(1-q)^2u_0 + \pi q^2u_1 + (1-\pi)(1-q)^2u_0 \\
=&2\pi(1-\pi)q(1-q)(u_1 - u_0) - (1-\pi)(1-q)^2u_0 + \pi q^2u_1 > 0
\end{aligned}$$

1.B Appendix: Organizational Forms in Entrepreneurial Finance

1.B.1 Interviews with Venture Capital Firms

We conducted semi-structured interviews with current and former investment team members at 19 venture capital firms. The purpose of these interviews was to better understand the functional nature of the organizational decision-making process within venture capital firms. We contacted 113 alumni of a mid-Atlantic university, predominantly graduates of its highly ranked business and engineering programs, and we were able to set up interviews with 22 individuals. The individuals spanned all levels of seniority within their organizations, ranging from associate up to senior general partner. Some individuals had worked at more than one venture capital firm during the course of their career, and they were thus able to speak about more than one firm. In some cases, we interviewed multiple employees of the same firm.

Interviews took place over June and July 2014, and each interview was approximately 30 minutes long. Informants were ensured anonymity of themselves and their firms. The interview data was supplemented with data available from CrunchBase, the Investment Advisor Public Disclosure (IAPD) database, Thomson ONE, and company websites.

The main finding of the interviews is that all venture capital firms have an organizational routine for integrating information from its employees and evaluating deals sourced by those employees. There is unanimously a group stage that requires some or all of the other partners to vote and confirm the deal before it is executed. However, there is tremendous heterogeneity about how the information is integrated and how group voting processes work, particularly in the degree of formality used.

Firms ranged from allowing partners to individually execute investments with relative little oversight by the other partners besides a brief discussion at the partner meeting, to having a formal and tracked voting process requiring a specific number, majority, or unanimous vote of the partners. There is also heterogeneity in who is allowed to vote: some firms allow all people with the title of partner to vote, and other firms have a specialized investment committee involving a subset of the partners to vote. At the extreme, one firm requires all deals proposed by partners to be voted upon by only one specific partner. Formal reporting of the results of the interviews are forthcoming.

1.C Appendix: Data

1.C.1 Testing Org. Structure Assumptions

Finally, to further test the validity of our assumptions on organizational structure, and in particular the voting mechanisms, we introduce two moderators, power concentration and venture fund availability.

Fund Availability

To test for implications of variation in the voting structure, we build a measure of fund availability to the venture capital firm. When funds in the venture capital firm are tight, we would expect the firm to act on a stricter voting rule if the deal flow remains constant. We exploit the venture capital fundraising cycle to develop a measure of fund availability. Using fund data from Thomson One, we assigned a value of available funds to the venture capital firm. Starting from the fund vintage year, the year a fund is finalized and makes its first investments, we assign the full value of the size of the fund, and then every year after that we take off 10% of the starting value of the fund, such that it is fully exhausted in 10 years. For firms with multiple funds, we take the same method, but sum across the proportionally exhausted fund values each year. This variable is based on the fairly strong assumption that all funds last 10 years and that the funds are disbursed evenly across those 10 years. Unfortunately, we do not have data on fund closing years or on exact investment sizes. As with the geographic distance, the venture capital fund size is also heavily skewed, and we used the log of venture capital fund size in our analysis.

The results of this analysis are presented in Table 1.9 and Figure 1.6. These results document the impact of fund availability by the venture capital firm on the probability the firm would pass over investments and leave it to their partners. The smaller the funds available to the venture capital firm, the more likely it is to be passed to the partners for consideration, but this result is insignificant.

Insert Table 1.9

Insert Figure 1.6

Power Concentration

A counter story to the information story we argue is one of incentive misalignment: perhaps the partners are withholding possible deals from their firm. If this were true, we would expect to find that partners who hold little to no ownership in their employing VC firm, to have stronger financial performance in their angel investments than their employer. To study power concentration, we collect data to identify the "true" partners of the venture capital firm are. Venture capital firms use the title of partner for many more employees than those that have significant ownership in the firm. For example, First Round Capital, a Philadelphia based seed stage venture capital firm, has 7 employees with the title of partner, but only one, Joshua Kopelman, holds any significant ownership stake in the firm itself. We utilize records from the Investment Advisor Public Disclosure (IAPD) database from the US Securities and Exchange Commission. They collect state and federal filings made by investment advisor firms, e.g. hedge funds and private equity fund management firms. As part of the filing, they must disclose who their direct owners, indirect owners, and executive officers are. All firms must disclose any c-suite officers (CEO, CFO, etc.). Those firms organized as a corporation must disclose any owner of 5% or more of the voting securities. Firms organized as a partnership must disclose all general partners and those limited and special partners that have the right to receive upon dissolution, or have contributed, 5% or more of your capital. We define "true" partner as any partners named in the IAPD disclosure. This study is omitted from the current paper.

1.C.2 Missing Data

To test whether we should be concerned about the missing data on founding teams, we conduct a basic test of missing data. There is a weak, mostly insignificant correlation between the team data missing, and the variables that we do have for the full sample (round age, future rounds, exit events), exhibiting a pattern consistent with data that is missing at random (MAR).

———————**Insert Table 1.10**———————

Chapter 2

Skilled Immigration and Firm-Level Innovation: Evidence from the H-1B Lottery

Andy Wu

2.1 Introduction

Does skilled immigration have a positive impact on domestic innovation at the firm level? There are two schools of thought on the subject. On the one hand, proponents of expanding skilled immigration claim that there is a shortage of domestic technically skilled labor and that skilled immigration increases technological innovation; innovation is a key driver of economic growth (e.g. Solow, 1956; Swan, 1956). Laszlo Bock, the Senior Vice President of People Operations at Google argues that "talented foreign-born individuals have played and will continue to play a vital role at Google and throughout our economy" and that restrictions on "our immigration policies are stifling innovation" (Bock, 2013). Indeed, the observational evidence is striking: some 42 percent of Fortune 500 firms were started by immigrants or their children; these 211 firms produce over $5 trillion in revenue annually (Ballmer et al., 2011). On the other hand, opponents of skilled immigration expansion, particularly from organized labor, argue that the H-1B program crowds out domestic employees and suppresses domestic wages. Richard Trumka, President of the AFL-CIO wrote that "High-tech companies say there are 'too few' American high-tech workers, but that's not true. . . They want a massive expansion of H-1B visa holders because they can pay them less. . . This is not about innovation and job creation. It is about dollars and cents" (Trumka, 2013). If we cannot find that the skilled immigrants are productively superior to domestic labor, such as in generating technological innovation, it becomes harder to justify the H-1B program, particularly if foreign labor is just a direct substitute for domestic labor and thus depressing domestic wages (e.g. Samuelson, 1964).

Further empirical understanding of skilled immigration is necessary to guide US public policy as immigration grows in importance to employers. Many developed countries explicitly recruit highly skilled immigrants without placing limits on the number of skilled immigrants that may come, while the United States allows only a limited number, primarily through the H-1B program.[1] In 2014, more than half of H-1B applications were denied to satisfy the statutory caps, representing the rejection of a substantial number of mutually beneficial transactions between foreign workers and domestic employers. Demand for highly skilled immigrants has steadily risen, possibly reflecting a dwindling technical capacity of U.S. domestic graduates (Bound

[1] Australia, Canada, Japan, South Korea, the United Kingdom, France, the Netherlands and Germany place no cap on their high-skills immigration (Ochel, 2000).

et al., 2009).

The literature on skilled immigration and technological innovation (as measured by patent counts) has consistently found a positive relationship between the two. Hunt and Gauthier-Loiselle (2010) find a 1 percentage point increase in immigrant college graduates' population share increases patents per capita by 9-18 percent. Hunt (2011) finds that immigrants entering on a student/trainee or temporary work visa have higher patent productivity, publishing productivity and company founding rates than American-born workers. Kerr and Lincoln (2010) find that higher aggregate H-1B admissions increase immigrant employment and patenting in their study of city-year variation in H-1B dependence. Chellaraj et al. (2008) study variation in enrollment in U.S. graduate programs by international versus domestic students and find that a 10% increase in foreign graduate students leads to 6.8% more patent grants to universities and 5.0% more to non-universities. The prior literature is dominated by empirical work using data at the regional level, instead of at the level of individual firms. This type of regional analysis may be susceptible to various confounding factors, such as macroeconomic shocks.

In this study, we address these limitations by focusing on the firm-level effects of skilled immigration. Specifically, we evaluate the impact of skilled immigration on U.S. innovation by exploiting a random lottery in the H-1B visa program. We compare firms that applied for the same number of lottery-subject applicants but won different numbers of immigrants because of the lottery. We then compare patents across these firms to identify the impact of these immigrants.

We find that winning an H-1B immigrant does not significantly increase patent applications or grants at the firm level. Our results suggest the existing literature, which shows a positive correlation between the spatial distributions of skilled immigrants and patents, cannot be associated with a direct firm-level effect. We argue that our results are justified and should be expected, given the pervasive use of the program in industries where patenting is not the main value-appropriation strategy. Thus, empirical patent measures are not a true measure of innovation for this setting.

In parallel to our study, Doran et al. (2015) also implement the H-1B lottery for identification of firm-level impact of skilled immigration, but they use a different econometric strategy involving instrumental variables and focus on patent grants and the lottery years of 2006 and 2007. We also include the 2008 lottery, the largest of the 3 years. Beyond just patent grants, we also examine patent applications, giving us a longer time window for analysis: because of a significant lag between patent application and patent grants, patent grants may be insufficient to observe immigrant effects on patents in the relatively recent time period of 2006–2008, making the patent application data useful for enlarging the sample and ruling out patent approval lags as an explanation for the null effects. Similar to our findings, they report an insignificant correlation between H-1B lottery wins and patenting using a different identification strategy. Across various specifications, we also find insignificant and near negative effects of H-1B immigration on firm-level patent grants and patent applications.

This paper contributes to a small but growing literature on the impact of skilled immigration on innovation and firm productivity. Our paper is the first to use administrative patent application records in conjunction with H-1B administrative data to estimate the causal impact of an H-1B immigrant on firm-level innovative productivity. We also provide information about the behavior and strategies of firms and immigrants participating in the H-1B program and provide policy recommendations surrounding the program.

Our paper proceeds as follows. In Section 2.2, we describe the institutional details of the H-1B visa program. In Section 2.3 and Section 2.4, we elaborate more on the H-1B lottery, which forms the basis of our empirical design, and explain the associated econometrics. In Section 2.5, we detail our data collection and construction. In Section 2.6, we present our main results. In Section 2.7, we discuss institutional details that may have driven other positive findings and argue for tempered optimism regarding the innovative benefits of the H-1B program. In Section 2.8, we conclude.

2.2 H-1B Program

Firms apply for H-1B visas on behalf of skilled foreign workers they would like to hire domestically. The H-1B visa program—administered by the United States Citizenship and Immigration Services (USCIS)—enables U.S. employers to seek temporary foreign workers in a *specialty occupation*, an occupation that "requires theoretical and practical application of a body of highly specialized knowledge in fields of human endeavor."[2] The visa application fees are paid for by the employer, and the fee and accompanying legal services generally cost several thousand dollars per visa petition filed. The visa lasts for three years but can be extended to six years by the employer. It is officially classified as a non-immigrant visa—i.e., for those not seeking long-term permanent residency—but it works as a "dual intent" visa, meaning it enables its holder to seek lawful permanent resident status through a green card. Administratively and throughout this paper, the H-1B sponsoring firm is referred to as the *petitioner*, while the foreign worker is known as the *beneficiary*. A visa application is referred to as a *petition*. The visa ties workers' legal status to their continued employment at the firm; if the worker quits or is fired, the worker must secure another visa or may be required to leave the country. The H-1B program contains a number of measures designed to protect the employment and wages of domestic workers, codified

[2] As stated in the U.S. Code of Federal Regulations "Special requirements for admission, extension, and maintenance of status" in 8 CFR§214.2(h).

in the Labor Condition Application (LCA), which is self-attested by the petitioners.[3]

2.3 H-1B Lottery

Our empirical design exploits an idiosyncratic property of the H-1B program that led to randomization of visa issuance. The Immigration Act of 1990 established a cap on the number of new H-1B visas that can be issued each year. Congress sets the cap for each year, which normally exists at 65,000 visas with a separate cap, known as the "advanced-degree cap exemption," for 20,000 immigrants with a master's degree or higher. In this paper, we focus on only the 65,000 non-advanced degree visas that are subject to the regular cap. At the beginning of the 1990s, the number of available visas exceeded the number of petitions, but the number of petitions rose until the mid-1990s, and the cap became binding. The cap was raised in 1998 and 2000, reaching a high of 195,000 visas and becoming non-binding again in many years. However, this high cap was not renewed, and by 2004, the cap returned to the original 65,000 and became binding again for non-advanced degree holders.

The program operates on a first-come, first-serve basis, so the petitions that arrive earlier in the mail take priority. USCIS begins accepting petitions for H-1B visas for the next year on the first business day of April in the current year. As expected, firms began to apply earlier as demand for visas increased. In 2005, the available cap-subject visas ran out in 132 days. By 2006, the visas ran out in 56 days, and in 2007 and 2008, the entire supply of H-1B ran out within days of the application cycle

[3]The Labor Condition Application (LCA) requires that employers attest to the following conditions. First, the immigrant's wage must meet or exceed the prevailing wage for the majority of employees in their area of employment. Second, the hiring of the immigrant must not adversely affect working conditions of workers similarly employed. Third, the immigrant cannot be employed in an occupation and place of employment where there is currently a strike, lockout or work stoppage. The American Recovery and Reinvestment Act of 2009 added a number of other restrictions, including that employers must take good-faith steps to recruit U.S. workers for the open position and that they must not have laid-off and will not lay-off any U.S. worker in an equivalent job.

opening. In 2006, 2007, and 2008, they received far more petitions than they had available visas in those initial days. Because USCIS cannot distinguish which petitions had arrived in the mail earlier, they subjected H-1B petitions received after the application cycle opened but before the "final receipt date" to a "computer generated random selection process" to determine which petitions were approved and which were not. We refer to the random selection process as the *lottery*.

In 2007, the quota was exceeded, almost twice over, in the first two days of the application cycleby the second day, 123,480 applications for H-1B visas were submitted to USCIS. A lottery was used to randomly allocate 65,000 visas among the many petitions. In 2008, the quota was exceeded by April 7, and winners were randomly drawn from the application pool of those who filed for H-1B visas from April 1 to April 7. We exploit the use of these lotteries for our empirical design.

2.4 Empirical Design

The empirical design leverages the H-1B lottery to address selection bias that may have impacted previous estimates of the effect of skilled immigration on patenting. We base our main regression model on Black et al. (2003), who leverage random assignment in the unemployment insurance system, and Angrist et al. (2012), who study charter school lotteries in Boston. To isolate random variation from the lottery, Angrist et al. (2012) condition on "risk set" indicators designating the combination of schools each student applied to. Conditional on the risk set, winning in the lottery is random.

In the simplest analysis, we could compare the patent outcomes of firms who petitioned for the same number of H-1B immigrants but won different number of H-1B visas because of the lottery. This approach has limited statistical power due to the small number of firms that applied for the exact same number of immigrants. Instead we pool these regressions using a fixed effect for each observed number of applications for a firm, thus making comparisons only among firms that applied for the same number of visas.

Firms petition for multiple H-1B visas for foreign workers. The number of H-1B visas a firm wins in the lottery is not unconditionally random. The number of H-1Bs a firm wins, however, is random conditional on how many applications they submit. Thus we specify the statistical model to compare the mean patenting of firms winning more lotteries within a group of firms who petitioned for the same number of H-1B visas. In all our analysis, we study three separate lottery events, in 2006, 2007, and 2008. For firm s, year t, petition count j, lottery year Y, and patent lag k, we estimate:

$$y_{s,t+k} = \alpha + \beta\theta^Y_{st} + \sum_j \delta_j d^Y_{sj} + \epsilon_{st}$$

We refer to this model as the "Petition Bin" model. $y_{s,t+k}$ represents the number of patents a firm applies for or is granted for the k years after the lottery, θ^Y_{st} represents the number of H-1B immigrants an employer won in year Y, and d^Y_{sj} represents a dummy that equals 1 for firms with petition count j and 0 otherwise for firms in the Y lottery. β captures the average effect of one additional H-1B immigrant on a firm's patenting behavior in one year. This model represents the most parsimonious use of the risk set, which pools data across firms with different numbers of petitions to increase statistical power. The Petition Bin model is estimated using ordinary least squares (OLS).

Conditional on the number of petitions a firm submits, θ^Y_{st} approximates a binomial random variable. The proportion of available visas relative to the total number of petitions defines the probability p that a particular petition will be successful and be awarded a visa. The number of petitions a particular firm files is denoted as n. A firm with full information and competent paperwork ability will expect np successes with variance $np(1-p)$.

To check robustness, we compare the results of this petition bin specification to those of a generalized differences-in-differences with firm fixed effects to controls for pre-existing differences in firms and absorb more residual variation to improve efficiency and account for pre-existing differences between lottery winners and losers. If the lottery is not truly random or our designation does not isolate lottery-induced rejections, the generalized differences-in-differences model controls for a baseline patent rate and addresses that issue. This model controls for underlying time-invariant firm quality. For firm s, year t, and lottery Y, we estimate:

$$y_{st} = \alpha + \beta\omega_{st}^{Y} + \zeta\pi_{st}^{Y} + \gamma_s + \lambda_t + \epsilon_{st}$$

We refer to this as the "Diff-in-Diff with Firm FE" model. The variable y_{st} represents the patent count of firm s at time t. The variable ω_{st}^{Y} represents the number of lottery wins the firm won in Y if $t \geq Y$; for all $t < Y$, ω_{st}^{Y} is equal to 0. π_{st}^{Y} represents the number of H-1B petitions made by the firm in Y if $t \geq Y$. For all $t < Y$, π_{st}^{Y} is equal to zero. The variables γ_s and λ_t represent firm and year fixed effects respectively. The firm fixed effects still function as risk sets, but they are a more generalized control than the risk sets based upon petition bins.

Finally, we implement another model that replaces the firm effects with petition bins (which would otherwise be collinear with the firm fixed effects). For firm s, year t, petition count j, and lottery Y, we estimate:

$$y_{st} = \alpha + \beta\omega_{st}^{Y} + \sum_{j}\delta d_{sj}^{Y} + \lambda_t + \epsilon_{st}$$

We refer to this as the “Diff-in-Diff with Petition Bins” model. d_{sj}^{Y} represents a dummy that equals 1 for firms with petition count j and 0 otherwise. As before, the variable y_{st} represents the count of patents for firm s at time t. The variable ω_{st}^{Y} represents the number of lottery wins the firm won in Y if $t \geq Y$; for all $t < Y$, ω_{st}^{Y} is equal to 0. This model is less general than the firm FE model—and it may underperform if the lottery is not truly random—but it would control for non-randomness of lottery if the non-randomness is predicted by the number of petitions made, which can be thought of as a proxy for firm size.

We estimate our differences-in-differences models with ordinary least squares (OLS), OLS with a logged dependent variable (e.g. $\ln(\text{Patent Count} + 1)$), and negative binomial (NBR) with conditional firm fixed effects. First, the OLS model is the most transparent and best linear unbiased estimator, but inference on the parameters requires a normality assumption, and the patent count dependent variables are clearly non-negative and heavily skewed with long right tail: this non-normal distribution causes inefficiency in the basic OLS model. Second, logging the dependent variable of patent count is a rough improvement to the performance of OLS as it makes the dependent variable more normal.[4] Third, the negative binomial distribution allows for count data with different means and variances, and it is commonly used to analyze patent data (Hausman et al., 1984; Allison and Waterman, 2002). We provide robust standard errors for all our regression models.

[4]We add 1 to the patent count before we take the ln to address values of 0 in the dependent variable that would otherwise be undefined when logged. This modification makes ex-post interpretation of the coefficient slightly more nuanced, as it doesn't easily fit the percentage change interpretation of logged regression variables that is traditionally used.

2.5 Data

We construct our dataset from U.S. Citizenship and Immigration Services (USCIS) administrative records and U.S. Patent and Trademark Office (USPTO) patent records. The administrative records were obtained through five Freedom of Information Act (FOIA) requests made from 2012 to 2014. Our original dataset contains the universe of H-1B petitions from 1999 to 2012 (3.6 million petitions) with information on the final decision regarding each petition. We manually check firm names to correct for errors and to aggregate petitions made by clear subsidiaries of larger entities.

We replicate the lottery sample for the years of 2006, 2007, and 2008 from the full set of petitions. First, we limit the sample to the set of petitions with receipt dates before or on the "final receipt date" as announced by the USCIS in their press releases. Second, we eliminate petitions from non-profit entities. Third, we drop beneficiaries with technical masters and Ph.D. degrees as they would be exempt from the regular cap and thus would not be subject to the lottery. Fourth, we retain regular filings (not changing status, extending stay, or amending stay) made for new employment. Finally, we keep only petitions on behalf of beneficiaries not currently in the U.S. to create the strictest sample possible. While this sample largely represents the full H-1B lottery, one drawback of this method of data construction is that we cannot fully distinguish between petitions declined because of bureaucratic issues (such as failing to correctly fill out an employer identification number) and those declined because they were not chosen in the lottery. The number of these bureaucratically declined applications is small relative to the lottery and as the petition is usually completed by expert legal help, rejections should be stochastic and not reflect the intrinsic quality of the petitioning firm. As a robustness check, we implement a generalized differences-in-differences model to control for underlying time-invariant firm quality.

Our patent grant data is from the IQSS Patent Network database (Li et al., 2014) and our patent application data is from the USPTO/Google Patent Application Publication dataset, available from 2001. The IQSS Patent Network database extends until the end of 2013. We fuzzy match petitioning firm names with patent assignees using the Microsoft Research and Microsoft Business Intelligence algorithm at a 0.85 level (Arasu et al., 2011),[5] which we then manually check. We do so separately for the IQSS and Google Patent data. We were unable to use citation-weighted patent counts (Trajtenberg, 1990), commonly considered to be a better measure of innovation impact, because there is not enough of a time window after the lotteries. Another limitation is that we only see patents granted up to 2013, and we can only observe patents up to those granted in late 2010, although that is not a complete sample either as many patents applied for in 2010 have not been granted yet if the process took longer than three years.

We also include patent applications in our study to give us a longer time window after the lottery event. Patent grants may understate the effect of H-1B immigration on innovative productivity as a long review period truncates what we can observe. Between 1976 and 1996, patent applications took anywhere from 1 to 1,143 months to be granted, with a mean of 28.4 months (Popp et al., 2004), with variation driven mostly by idiosyncratic factors, although there is systematic variation in patent grant lag across technological classes. Assuming the lottery is uncorrelated with the patent grant lag across technological classes, our results are not biased by different lag lengths in different technological classes. Given that our patent grant data only extended until the end of 2013, based upon a two to three year patent grant lag, we have a four year

[5] Arasu, Chaudhuri, Chen, Ganjam, Kasushik, and Narasayya at Microsoft developed the fuzzy matching technology that made this project possible. We leave it to the reader to recognize the irony of this.

window of observation for our 2006 lottery (2007–2010) and a three year window of observation for our 2007 lottery (2008–2010), with many patent grants missing at the tail end of the observation window as some patent applications have not been granted yet. We do not use the 2008 lottery in our study of patent grants because of the short post-lottery observation window, but we do study the impact of the 2008 lottery on patent applications. We introduce patent applications to give a larger observation window up until 2012. Patent applications of course do not fully translate into patent grants, and some applications are rejected in the process. The grant rate is fairly high though, as 72.3% of patent applications filed in January 2001 were published before April 2006 (Lemley and Sampat, 2012).

The descriptive statistics are presented in Table 2.1. The data summarized here is structured as a balanced firm-year panel from 2005 to 2012. Patent grant data are available only up until 2010, and patent application data are available up until 2012. To gain a sense of patent productivity of the average firm and the average interaction with the lottery, in 2008 the average firm in the lottery submitted 1.7 patent applications and received 1.3 patent grants. In the same year, the average firm submitted petitions for 6.3 and won 4.4 visas in the lottery.

Insert Table 2.1

To assess whether the lottery was random, we implement a placebo test in which we regress lagged patents granted on the lottery win share; results of this test are in Table 2.2. The regression demonstrates that there is a precise zero correlation between the firm's pre-lottery patent rate and the share of applications the firm won in the lottery. The consistent zero-results suggest a random lottery.

Insert Table 2.2

2.6 Results

In the baseline specification, winning an H-1B petition has no statistically significant effect on patents granted to the firm. The coefficients are small, insignificant and fall on either side of zero. Table 2.3 presents the regression results for the Petition Bin model with a dependent variable of patent grants by the firm. The top row shows the estimated effect of an H-1B win on patents granted in that column's year. The estimates to the left of the vertical bar function as placebo estimates. The estimate reflects the average effect of one additional H-1B worker on the number of patents a firm has been granted in that year.[6] The last column reflects the average per-year effect of an H-1B worker after the lottery. Because there is a significant lag between patent application and patent grant, the grant measure may understate the effect of H-1B workers since a patent the immigrant contributed to would not even be reviewed within the observable patent data. We incorporate data on patent applications, which does not have the review lag.

Insert Table 2.3

Table 2.4 presents a similar exercise as Table 2.3 but the dependent variable is patent applications rather than patent grants. Again, our results are primarily insignificant, with the notable exception of the 2008 lottery. The effect is very close to zero in the 2006 lottery, grows to 0.08 in the 2007 lottery, and becomes statistically significant and positive in the 2008 lottery. We find that the patent-application productivity is higher for firms that win the 2008 lottery, even before the lottery, shown in columns (18) and (19) of Table 2.4. There are two possibilities to explain this phenomenon.

[6] While the results are statistically insignificant, the coefficient on *Wins in 2007* in column (12) would imply that an average firm that won one additional H-1B worker would receive 0.003 additional patent grants three years later in 2010 (but this is not statistically significant and should not be interpreted as such).

First, the lottery could have randomly selected higher productivity firms; the differences are consistently significant at least the 10% level; it is possible that the lottery randomly selected firms with a higher pre-lottery patent-application productivity and indeed would happen in one of ten draws. A second possibility is that the lottery was not random in 2008. A possible but untested explanation could involve the competitive political environment of the 2008 general election, where USCIS may have incorporated political pressures to accommodate influential firms.

Insert Table 2.4

Given our results for 2008, our main concern for identification is that either the lottery is not truly random, or our method of identifying lottery-rejected firms sometimes includes firms that were rejected because of incomplete paperwork. To control for this, we implement a generalized differences-in-differences design with firm fixed effects and with petition bins that would yield unbiased results even if the lottery were non-random (if some firms are better at winning the lottery than others). The results from this specification are largely the same, but the coefficient estimates are even smaller, usually insignificant, and sometimes negative and significant, as presented in Table 2.5, with a dependent variable of patent grants, and Table 2.6, with a dependent variable of patent applications. We find some significant results on our OLS Log DV models. The coefficient on the logged dependent variable represents the approximate percentage change in patents, so Table 2.5 model (2) is interpreted as showing a 2% reduction in patenting for an additional H-1B visa won, significant to the 5% level. The 2008 results shift downward in the differences-in-differences framework, suggesting that: the lottery randomly chose more productive firms in 2008; the lottery is not truly random; or our classification of lottery rejections is inaccurate in some cases.

Insert Table 2.5

Insert Table 2.6

Another avenue for exploration is that of firm behavior: firms may adjust their H-1B petition filing strategy based upon the previous year's success or failure. Our estimated effects would be understated if, for instance, firms that lose the lottery apply for more visas the next year; in this case, the firm is only without the productive capital of an H-1B worker for a single year. Randomly winning (losing) a visa in 2007 would decrease (increase) the number of applications submitted in the next year 2008. On the other hand, our estimates may be overstated if there were returns to scale in hiring skilled immigrants; in this case, randomly winning a visa in 2007 would be positively correlated with the number of petitions a firm submits in 2008, or in other words, winning (losing) one visa in 2007 increases (reduces) the firm's H-1B petition filings in 2008. We find that an additional H-1B visa received in 2007 causes firms to petition for more visas in 2008, as shown in Table 2.7; one additional H-1B visa won in the 2007 lottery causes the average firm to apply for about 0.2 more H-1B visas the following year 2008, significant to a 5% level.

Insert Table 2.7

The null results are striking in the context of the existing literature, the majority of which demonstrates a robust positive relationship between the H-1B program and patenting. Some caution is needed in interpreting our particular results. The estimates reflect the average effect of a non-master's degree H-1B immigrant on patent applications and grants. The results do not, for instance, speak directly to the impact of the subset of skilled immigrants educated at elite American universities, as many of the immigrants were educated at foreign universities of variable quality. More importantly, our study focuses only on the effect of H-1B visas subject to the lottery, i.e. those without a relevant master's or doctorate degree; petitions for immigrants with that higher level of education beyond the bachelor's degree are considered in a different pool of visas, and thus not subject to the lottery.

2.7 Why Don't H-1B Immigrants (in the Lottery) Produce Patents?

The results prompt two questions: Why have previous studies demonstrated large positive associations? And why would an H-1B win have no effect on patent productivity?

2.7.1 What is Different about the Prior Research?

First, we proffer that a number of other factors besides the direct effect of an immigrant being placed into a firm may be driving prior results. Our leading hypothesis is that results from studies without a credible control group were unable to control for significant determinants of patenting productivity. Perhaps the most persuasive paper, Kerr and Lincoln (2010) show that there were large increases in the rate of Indian and Chinese patenting in cities and firms that depend on H-1B visas when H-1B visa availability expanded. The lottery results suggest that these effects may be driven by an omitted variable, like productivity shocks, which increase both a firm's patenting and a firm's interest in H-1B workers. As an example, imagine that prolific scientists enter some firms, which increases the firm's patent rate and the firm's demand for technical labor, creating a spurious correlation between H-1B workers and patent creation.

It is also possible that the patenting effects may exist in neighboring firms via spillovers. Regional data on H-1Bs and patenting behavior would be able to capture spill-over effects, which we would not observe here, but it would be captured in prior studies that study the regional impacts of H-1B immigration. However, it seems unlikely to be the case that an immigrant would have no effect on her own firm but have substantial effects on surrounding firms she has even less to do with, in a time span of a couple years. A more probable story for possible spillovers comes from when immigrants employed by one firm are then contracted out to other firms. Thus the additional lottery wins would not be observed as having an impact on patents at the firm that won the visa. Later in this section, in Figure 2.5, we address this issue further.

2.7.2 Why Zero Estimates?

We use our detailed data on petitions to shed light on why the effects are plausibly zero. The following figures contain data from our sample of petitions from 1999 to 2012, including both lottery and non-lottery petitions.

Figure 2.1 shows the distribution of firm types participating in H-1B program. 48.8% of petitions originate from computer-related firms. The next largest categories are Architecture & Engineering (12.2%), Education (9.6%) and Administrative Specializations (8.4%). Life Science firms account for 2.71% of the petitions. Typically we do not expect any impact on firm-level patenting from educational or administrative firms because they are not traditionally heavy in research and development that would lead to patents.

——————**Insert Figure 2.1**——————

Figure 2.2 shows the distribution of occupation types (as defined in the Dictionary of Occupational Types by the US Department of Labor) in H-1B petitions. Diving further into the occupations that beneficiaries are being placed into, we find that 42.9% of the occupations are in "Systems Analysis and Programming," which represents information technology support roles, which is clearly unlikely to generate intellectual property, and software engineers, which as we will also discuss, are also unlikely to generate substantial intellectual property.

————————**Insert Figure 2.2**————————

Patenting varies heavily by industry because a patent's ability to internalize the social benefits of innovation varies widely. Software has been known to have historically weak patent protection (Bessen and Maskin, 2009). In industries such as life sciences, chemicals, and semiconductors, patents have been more effective at protecting intellectual property arising from R&D, generating a greater value to patenting (Arora et al., 2008a).

Moreover, software patents are not predominantly generated by software firms. Bessen and Hunt (2007) construct a dataset of software patents and find that software patents tend to be assigned to firms in industries known to accumulate large patent portfolios and to pursue patents for strategic reasons (computers, electrical equipment, and instruments), particularly in manufacturing and not to actual software publishers, who only hold 5% of their sample of software patents. The manufacturing sector acquires 75% of software patents but employs only 11% of programmers and analysts. These patent portfolios are often part of "patent thickets," a set of overlapping patents for defense purposes by firms and for offensive purposes by patent assortment entities.

We also run our main analyses (Petition Bin Model & Diff-in-Diff) for the set of petitions by firms applying for immigrants specializing in life sciences occupations, where patenting is more common and a more effective measure of value capture. We find no significant effects. This result may be due to a lack of statistical power given the small sample size. But another possibility is that the set of cap-subject immigrants in life sciences may indeed have low patenting productivity. As legally defined, the set of cap-subject immigrants we are studying are those without master's degrees and doctorates (otherwise they wouldn't be cap-subject). It is hard to imagine that a life science employee with just an undergraduate degree would be very effective at generating patents in a field where a Ph.D. is so common and necessary training to conduct independent research. The more likely reality is that the cap-subject life science occupation immigrants are taking support roles in laboratories and not leading independent research.

We find that the patent classes represented by the firms participating in the H-1B program do not reflect the full distribution of patent classes. Figure 2.3 shows the 10 most popular patent classes among patents by H-1B firms and there is a clear lean toward software and information technology patents, which are less common in the full set of all USPTO patents.

——————**Insert Figure 2.3**——————

The distribution of H-1B immigrants is heavily skewed towards India, which has been historically known to produce a large amount of engineers, particularly in software (Banerjee, 2008). This distribution of H-1B beneficiary country of origin is shown in Figure 2.4. While not captured in our data, it has been noted that H-1B immigrants are younger than domestic employees who might otherwise take the occupation (Kerr et al., 2015). Greater age is found to be beneficial to innovative impact (Jones, 2010).

——————**Insert Figure 2.4**——————

Finally, we reflect on the distribution of visas that would occur in an expansion of the program. Figure 2.5 shows the top 10 largest filers of H-1B petitions in 2007. With the exception of Microsoft Corporation, the other nine companies are all what would be classified as information technology consulting firms, best known for outsourcing services. These firms provide services from foreign labor based located in a foreign country, which for these firms is usually India, and they are experts in navigating immigration procedures. Once they obtain a visa for these workers, the firms place the worker with a client. Because these firms are functionally working for another firm, the visa-sponsoring firm likely does not own patents resulting from the immigrant. We have no way of ascertaining the identity of their clients and placement of the immigrants.

Insert Figure 2.5

To summarize, we believe the academic literature has misinterpreted the practical use of H-1B program. The majority of firms do not hire H-1B immigrants to generate patents. The average H-1B immigrant is a young Indian software engineer or information technology support specialist and not a patent-generating researcher or scientist, and many of these immigrants are not even employed by their hosting firm.

2.8 Conclusion

We estimate the causal impact of H-1B workers on the patent production of American firms by exploiting a lottery that *randomly* issues visa to petitioning firms. We find that traditional H-1B immigrants (no relevant master's or Ph.D.) have no observable impact on a firm's patent applications or patent grants. Using a rich dataset on the universe of H-1B petitions, we demonstrate that the H-1B program is primarily employed in firms and occupations that do not contribute to innovation as captured by patents. Our results provide new evidence on the impact and role of skilled immigration. Our result is surprising given a substantial prior literature demonstrating a robust positive correlation between H-1B visa use and patent production. These results are particularly important in light of an on-going debate surrounding the use of immigration to meet domestic labor demand.

The present work leaves much to be explored in the context of understanding the H-1B program and skilled immigration more generally. Our analysis focuses on the impact of H-1B immigrants without a relevant education beyond a bachelor's degree, and our results do not speak directly to the innovative value-add of highly skilled immigrants trained in prestigious American universities or the H-1B visas offered to immigrants with a master's degree. The role of the program for master's and Ph.D. educated immigrations needs to be further studied as the upper cap on that portion of the H-1B program is also reached. There are also other categories of the skilled immigration that have yet to be well studied, including the specialized H-1B1 program for Chile and Singapore, the H-1B2 program related to U.S. Department of Defense R&D, O-1 visa for individuals with "extraordinary ability or achievement." This paper should therefore be viewed as an intermediate step toward characterizing the impact of high-skilled immigration on American innovation and labor.

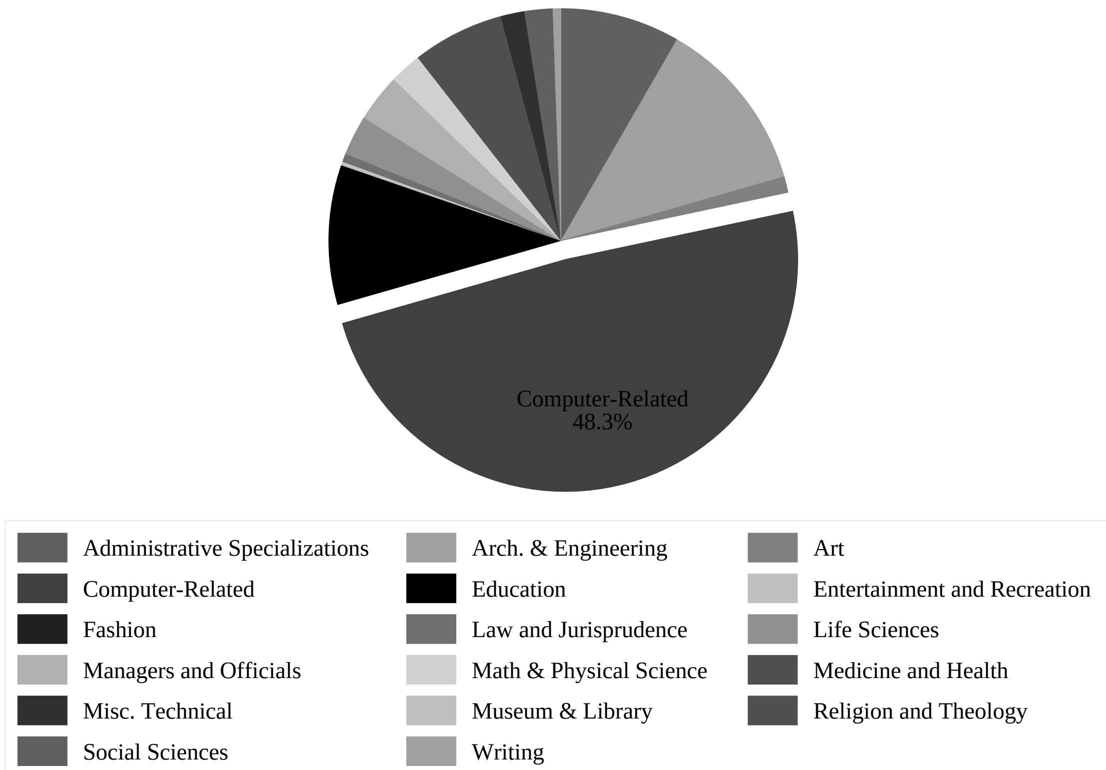

Figure 2.1: **Firm Industries**. This figure depicts distribution of firm industries who filed petitions in the H-1B program. The data is from United States Citizenship and Immigration Services (USCIS) and represents the full sample of H-1B petitions filed from 1999 to 2012.

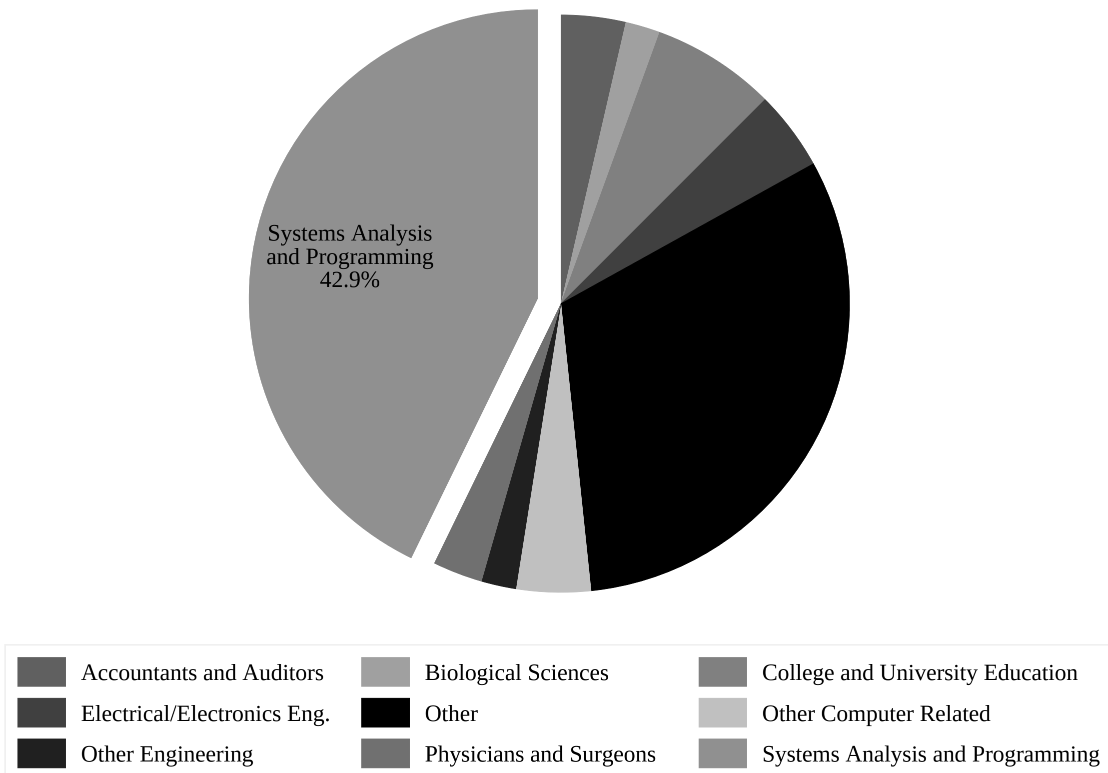

Figure 2.2: **Occupation Types**. This figure depicts distribution of beneficiary (immigrant) occupation types for petitions filed in the H-1B program. The occupation types are defined in the *Dictionary of Occupational Types* by the U.S. Department of Labor. The largest category, "Systems Analysis and Programming", represents information technology support roles, such as software developers and technical support. The data is from United States Citizenship and Immigration Services (USCIS) and represents the full sample of H-1B petitions filed from 1999 to 2012.

Class	Class Title	H-1B	USPTO
705	Data Processing: Financial, Business Practice, Management, or Cost/Price Determination	4.2%	0.7%
707	Data Processing: Database and File Management or Data Structures	3.1%	1.2%
514	Drug, Bio-Affecting, and Body Treating Compositions	2.4%	1.3%
435	Chemistry: Molecular Biology and Microbiology	2.4%	1.8%
370	Multiplex Communications	2.4%	1.7%
709	Electrical Computers and Digital Processing Systems: Multicomputer Data Transferring	2.1%	1.5%
455	Telecommunications	2.0%	1.7%
424	Drug, Bio-Affecting, and Body Treating Compositions	1.8%	1.0%
73	Measuring and Testing	1.5%	0.9%
340	Communications: Electrical	1.5%	1.0%

Figure 2.3: **Top Patent Classes**. This figure shows the top 10 most popular classes for patents filed by firms who filed at least one petition in the H-1B program from 1999 and 2012. The columns *Class* and *Class Title* are the official class number and name as defined by the United States Patent and Trademark Office (USPTO). is the The column *H-1B* represents the percentage of all the patents filed by H-1B participating firms in that patent class. The column *USPTO* represents the percentage of all patents in that patent class in patents applied for in the year 2007. The data is from United States Citizenship and Immigration Services (USCIS) and the United States Patent and Trademark Office (USPTO).

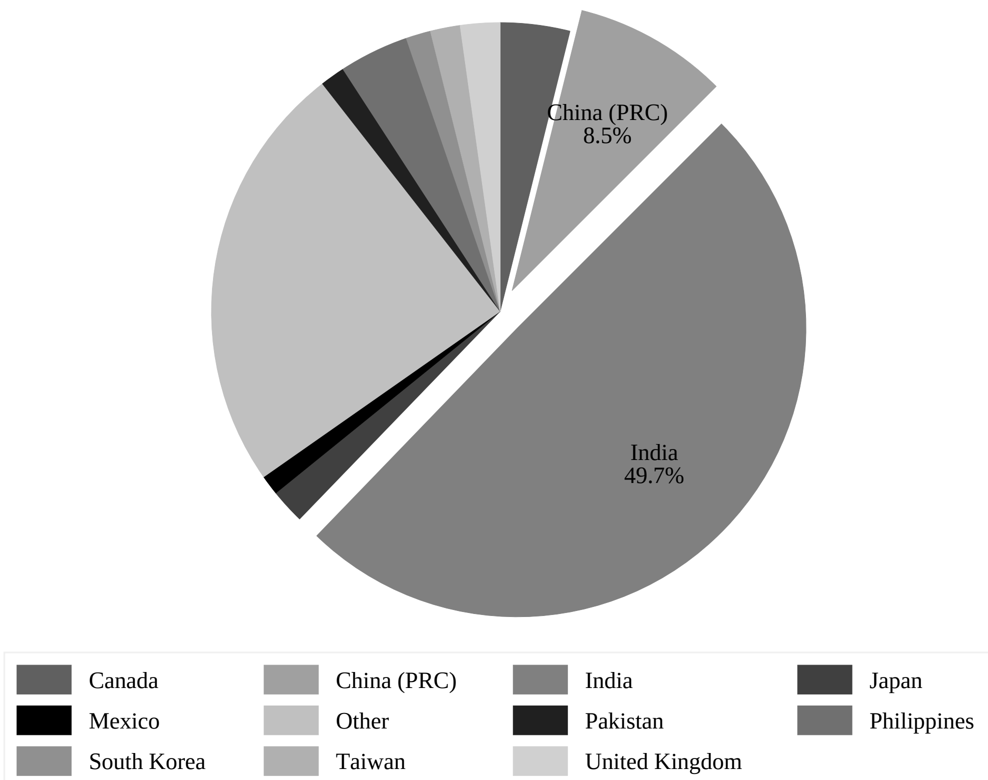

Figure 2.4: **Country of Origin**. This figure depicts country of origin of beneficiaries (immigrants) who had H-1B petitions filed on their behalf. The data is from United States Citizenship and Immigration Services (USCIS) and represents the full sample of H-1B petitions filed from 1999 to 2012.

Firm	**Petitions**
Infosys Technologies Limited	4175
Wipro Limited	2253
Satyam Computer Service Limited	1131
Cognizant Technology Solutions Corporation	979
Tata Consultancy Services Limited	576
Patni Computer Systems Limited	435
Microsoft Corporation	331
US Technology Resources, LLC	322
Accenture PLC	320
Larsen & Toubro Infotech Limited	257

Figure 2.5: **Top H-1B Petitioners**. This figure shows the top ten largest filers of H-1B petitions in 2007. With the exception of *Microsoft Corporation*, the other nine of top ten are information technology consulting firms, commonly associated with outsourcing services. The data is from United States Citizenship and Immigration Services (USCIS) and represents the full sample of H-1B petitions filed in 2007.

Table 2.1: **Summary Statistics**. This table presents summary statistics for our firm-year data composed of firms filing H-1B petitions in the 2006, 2007, and 2008 lotteries. H-1B petition data is from U.S. Citizenship and Immigration Services (USCIS), drawn from the compete set of H-1B petitions from 1999 to 2012 obtained via FOIA request. Patent grant data is from the IQSS Patent Network database (Li et al., 2014), and it is only available up until 2010. Patent application data is from the USPTO/Google Patent Application Publication system, and it is only available up until 2012.

2006	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Patent Grants	3.40	71.93	0	3152	6024
Patent Applications	5.79	107.39	0	3085	8032
Wins	2.26	5.40	0	90	10040
Petitions	2.88	6.27	1	96	10040
Share Won	0.77	0.37	0	1	10040
2007	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Patent Grants	1.45	32.39	0	3152	45720
Patent Applications	1.93	45.63	0	3085	60960
Wins	3.83	38.97	0	2242	76200
Petitions	6.02	58.96	1	4175	76200
Share Won	0.69	0.40	0	1	76200
2008	**Mean**	**Std. Dev.**	**Min**	**Max**	**Obs.**
Patent Grants	1.27	28.50	0	3152	42150
Patent Applications	1.74	38.50	0	3085	56200
Wins	4.36	50.93	0	2735	70250
Petitions	6.30	74.18	1	4778	70250
Share Won	0.73	0.39	0	1	70250

Table 2.2: **Lottery Placebo Test**. This table presents the results of the lottery placebo test. We regress patent grants filed by a firm in the year before the lottery on its share of wins for a given lottery in 2006, 2007, or 2008. This model is estimated using ordinary least squares (OLS). Statistical significance is represented by $*\,p < 0.10$, $**\,p < 0.05$, and $***\,p < 0.01$. Robust standard errors are shown in parentheses.

	(1)	(2)	(3)
Petition Win Share	**2006**	**2007**	**2008**
Patents	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)
Constant	0.766***	0.691***	0.730***
	(0.012)	(0.005)	(0.005)
Observations	1004	7620	7025

Table 2.3: **Petition Bin Model (Patent Grants)**. This table presents the results of the *Petition Bin* model with the dependent variable of *Patent Grants*. *All Years* contains all available post-treatment (post-lottery) years. This model is estimated using ordinary least squares (OLS). Statistical significance is represented by $*\,p < 0.10$, $**\,p < 0.05$, and $***\,p < 0.01$. Robust standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Patent Grants	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**All Years**
Wins in 2006	0.808	0.440	-0.037	0.036	-0.050	-0.005	-0.014
	(1.246)	(0.841)	(0.501)	(0.247)	(0.151)	(0.024)	(0.225)
Petition Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1004	1004	1004	1004	1004	1004	4016

	(8)	(9)	(10)	(11)	(12)	(13)
Patent Grants	**2006**	**2007**	**2008**	**2009**	**2010**	**All Years**
Wins in 2007	0.149	0.090	0.039	0.016	0.003*	0.019
	(0.112)	(0.067)	(0.026)	(0.010)	(0.002)	(0.012)
Petition Bins	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7864	7864	7864	7864	7864	23592

Table 2.4: **Petition Bin Model (Patent Applications)**. This table presents the results of the *Petition Bin* model with the dependent variable of *Patent Applications*. *All Years* contains all available post-treatment (post-lottery) years. This model is estimated using ordinary least squares (OLS). Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors are shown in parentheses.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Patent Applications	**2005**	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**All Years**
Wins in 2006	0.359	0.500	0.096	-0.053	-0.071	0.164	0.022	-0.096	0.010
	(0.493)	(0.927)	(1.278)	(1.349)	(1.003)	(1.367)	(0.952)	(0.343)	(1.008)
Petition Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1004	1004	1004	1004	1004	1004	1004	1004	6024

	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Patent Applications	**2006**	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**All Years**
Wins in 2007	-0.001	0.046	0.045	0.055	0.088	0.138	0.062	0.078
	(0.048)	(0.070)	(0.079)	(0.076)	(0.096)	(0.110)	(0.040)	(0.076)
Petition Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7864	7864	7864	7864	7864	7864	7864	39320

	(18)	(19)	(20)	(21)	(22)	(23)	(24)
Patent Applications	**2007**	**2008**	**2009**	**2010**	**2011**	**2012**	**All Years**
Wins in 2008	0.156*	0.192**	0.174**	0.203**	0.190**	0.059**	0.157**
	(0.083)	(0.091)	(0.084)	(0.096)	(0.085)	(0.030)	(0.071)
Petition Bins	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	7525	7525	7525	7525	7525	7525	30100

Table 2.5: **Differences-in-Differences (Patent Grants)**. This table presents the results of the *Diff-in-Diff with Firm FE* model—in the first 3 columns under the header *Firm FE*—and the *Diff-in-Diff with Petition Bins* model—in the last 2 columns under the header *Petition Bins*—with the dependent variable of *Patent Grants*. The *Diff-in-Diff with Firm FE* model is estimated with ordinary least squares (OLS) with firm fixed effects, OLS with a logged dependent variable ln(Patent Count + 1) and firm fixed effects, and negative bionomial (NBR) with conditional firm fixed effects. The *Diff-in-Diff with Petitions Bins* model is estimated with ordinary least squares (OLS) with firm fixed effects and OLS with a logged dependent variable ln(Patent Count + 1) and firm fixed effects. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors are shown in parentheses.

	Firm FE			**Petition Bins**	
	OLS	**OLS Log DV**	**NBR**	**OLS**	**OLS Log DV**
Patent Grants	(1)	(2)	(3)	(4)	(5)
Wins * Post (2006)	-7.181	-0.020**	-0.055	-2.114	-0.007**
	(6.518)	(0.009)	(0.090)	(2.328)	(0.003)
Petitions * Post (2006)	4.346	0.011*	0.042		
	(3.712)	(0.007)	(0.083)		
Observations (2004 to 2010)	6024	6024	498	6024	6024
Patent Grants	(6)	(7)	(8)	(9)	(10)
Wins * Post (2007)	-0.167	-0.001*	0.017	-0.040	-0.001***
	(0.214)	(0.000)	(0.013)	(0.046)	(0.000)
Petitions * Post (2007)	0.087	0.000	-0.017		
	(0.112)	(0.000)	(0.012)		
Observations (2005 to 2010)	47184	47184	4500	47184	47184
Patent Grants	(11)	(12)	(13)	(14)	(15)
Wins * Post (All)	-0.089	-0.000	0.014	-0.019	-0.000***
	(0.112)	(0.000)	(0.011)	(0.021)	(0.000)
Petitions * Post (All)	0.049	0.000	-0.014		
	(0.062)	(0.000)	(0.010)		
Observations (2004 to 2010)	77592	77592	6846	77592	77592
Firm FE	Yes	Yes	Yes	No	No
Petition Bins	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 2.6: **Differences-in-Differences (Patent Applications)**. This table presents the results of the *Diff-in-Diff with Firm FE* model—in the first 3 columns under the header *Firm FE*—and the *Diff-in-Diff with Petition Bins* model—in the last 2 columns under the header *Petition Bins*—with the dependent variable of *Patent Applications*. The *Diff-in-Diff with Firm FE* model is estimated with ordinary least squares (OLS) with firm fixed effects, OLS with a logged dependent variable ln(Patent Count + 1) and firm fixed effects, and negative bionomial (NBR) with conditional firm fixed effects. The *Diff-in-Diff with Petitions Bins* model is estimated with ordinary least squares (OLS) with firm fixed effects and OLS with a logged dependent variable ln(Patent Count + 1) and firm fixed effects. Statistical significance is represented by $*p < 0.10$, $**\ p < 0.05$, and $***p < 0.01$. Robust standard errors are shown in parentheses.

	Firm FE			**Petition Bins**	
	OLS	**OLS Log DV**	**NBR**	**OLS**	**OLS Log DV**
Patent Applications	(1)	(2)	(3)	(4)	(5)
Wins * Post (2006)	0.823	0.006	-0.064	0.338	0.003
	(1.021)	(0.006)	(0.100)	(0.352)	(0.002)
Petitions * Post (2006)	-0.414	-0.002	0.056		
	(0.612)	(0.004)	(0.092)		
Observations (2004 to 2012)	8032	8032	568	8032	8032
Patent Applications	(6)	(7)	(8)	(9)	(10)
Wins * Post (2007)	-0.036	-0.000	-0.000	0.002	0.000**
	(0.026)	(0.000)	(0.001)	(0.008)	(0.000)
Petitions * Post (2007)	0.026*	0.000***	0.000		
	(0.014)	(0.000)	(0.001)		
Observations (2005 to 2012)	62912	62912	4960	62912	62912
Patent Applications	(11)	(12)	(13)	(14)	(15)
Wins * Post (2008)	-0.092	-0.001	-0.001	-0.010	0.000
	(0.094)	(0.000)	(0.001)	(0.018)	(0.000)
Petitions * Post (2008)	0.058	0.000*	0.001		
	(0.053)	(0.000)	(0.001)		
Observations (2006 to 2012)	52675	52675	3976	52675	52675
Patent Applications	(16)	(17)	(18)	(19)	(20)
Wins * Post (All)	-0.031	-0.000	-0.001	-0.000	0.000
	(0.026)	(0.000)	(0.000)	(0.006)	(0.000)
Petitions * Post (All)	0.021	0.000**	0.000		
	(0.015)	(0.000)	(0.000)		
Observations (2004 to 2012)	103456	103456	7688	103456	103456
Firm FE	Yes	Yes	Yes	No	No
Petition Bins	No	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Table 2.7: **Firm Behavior**. This table presents the results of an ordinary least squares (OLS) regression with a dependent variable of *Petition Bins*, the number of H-1B petitions filed by a firm in 2008, and an independent variable of *Wins in 2007*, H-1B petitions awarded to the firm in 2007. *Petition Bins* fixed effects, representing petitions filed in 2007, are included. Statistical significance is represented by $* \, p < 0.10$, $** \, p < 0.05$, and $*** \, p < 0.01$. Robust standard errors are shown in parentheses.

	(1)
	Petition Bins
Wins in 2007	0.197**
	(0.091)
Petition Bins	Yes
Observations	2805

Chapter 3

R&D Production Team Organization and Firm-Level Innovation

Vikas A. Aggarwal
David H. Hsu
Andy Wu

3.1 Introduction

The expertise embodied in the stock of inventive human capital of a firm is critical to its innovation output, particularly in fast-moving entrepreneurial environments (Campbell et al., 2012; Hatch and Dyer, 2004; Eesley et al., 2014). Recent studies suggest that ongoing innovation in such settings is very often predicated on collaborative (rather than solo) production of knowledge by multiple individuals inside the firm (Wuchty et al., 2007; Jones, 2009), and that such team-based approaches are more likely to lead to breakthrough" innovations (Singh and Fleming, 2010). Team approaches, furthermore, resonate with popular accounts of the processes leading to innovation over the course of modern business history (Isaacson, 2014). Yet despite the importance of teams to the process of innovation in entrepreneurial settings, the strategy literature offers relatively little guidance as to how firms should *organize* their overall stock of human capital into teams in situations where firm-level innovation output is a desired outcome.

There are two key dimensions along which the prior literature has been limited in exploring the link between the organization of human capital into teams and firm-level innovation. First, while a rich body of work in the organizations literature has addressed issues such as the link between diversity (generally demographic) and team performance (e.g. Ancona and Caldwell, 1992; Williams and O'Reilly, 1998), it has typically done so by taking the team itself as the focal unit of analysis. Yet teams do not exist in isolation from one another; a focus on teams, if these teams are conceptualized solely as atomistic entities disembodied from an organizational context, may obscure the effects of interactions that occur across teams, with these interactions possibly shaping firm-level outcomes. Second, while a significant body of work in the strategy literature has examined the link between teams and performance, the focus on teams has been largely confined to addressing top management team (TMT) issues (e.g. Bantel and Jackson, 1989; Eesley et al., 2014), to the exclusion of issues that reside at the level of the firm's inventive output (i.e., production teams).

In this paper we focus on the firm-level implications of organizing inventor human capital (Cohen and Levinthal, 1990; Grant, 1996; Coff, 1997; Katila and Ahuja, 2002) into production teams with varied configurations. We ask the question: how do alternate approaches to organizing the diversity of technical experience contained in a firm's pool of inventors influence innovation outcomes at the firm-level? We argue that taking a firm-level perspective allows us to conceptualize technical experience diversity not only in the context of a given team (what we call "within-team" technical experience diversity), but more importantly in what we refer to as the dimension of "across-team" technical experience diversity.

To further elaborate on what we mean by these two forms of diversity, we illustrate in Figure 3.1 the point that a firm's total stock of technical experience diversity can be organized in alternate (though not mutually exclusive) ways. First, variation in the extent of diversity may exist *within* a team: inventors on a particular team may be more diverse or more uniform with respect to other inventors on that team. Second, such variation can be distributed *across* teams: the teams themselves can be conceptualized as being more diverse or more uniform as compared to the other teams. While studies on team design have examined diversity at the level of an individual team (e.g. Williams and O'Reilly, 1998), the within-firm, across-team perspective has received little attention. In addition, both dimensions of diversity have generally not been considered in light of the broader firm-level context and the associated design choices faced by managers. Our primary goal in this paper is to understand the relative net benefits to firm-level innovation output of these two diversity regimes.[1]

———————Insert Figure 3.1———————

In the next section we briefly discuss the background literature that motivates our empirical exercise, focusing in particular on why the concept of across-team technical experience diversity might be informative in the strategy literature, together with the key mechanisms—knowledge recombination and coordination costs—that we believe are likely to shape its effects. Our analysis draws on a sample of 476 venture capital-

[1]We consider across-team diversity and within-team diversity to be theoretically independent constructs. While we illustrate the "joint" condition (high on one dimension, low on the other) in Figure 3.1 for ease of exposition, for the purpose of our theory development we are focused on their independent effects.

backed biotechnology firms which we observe from their date of founding onwards, and for which we collect information on their inventors' full invention career experience. We begin by assembling a firm-year panel dataset that allows us to examine the effects of the two alternate technical experience diversity regimes with respect to firm-level innovation. To understand the mechanisms underlying our results we then reassemble our dataset to explore the effect of the alternate diversity regimes on inventor productivity using a difference-in-differences empirical specification at the inventor-year level.

Our results point to two key conclusions: (a) organizing teams with higher levels of across-team technical experience diversity results in greater benefits to firm-level innovation output than within-team technical experience diversity; and (b) the across-team effect operates via the lever of team stability, a measure of coordination costs. In a final section we discuss our results in the context of the broader strategy literature, focusing in particular on how the construct of across-team diversity might inform work in the domains of organization design, strategic human capital, and teams.

3.2 Theoretical Motivation

From the perspective of a manager concerned with firm-level innovation output, the task of organizing human capital into teams brings to light the dimension of across-team diversity. This concept has been relatively neglected in the literature on teams, where the focus has generally been on the team itself (versus the firm) as a unit of analysis (with a focus on the implications of within-team diversity consequently being paramount). Our development of the across-team diversity construct is an inherently firm-level one, which we argue will hold a host of theoretical implications at the intersection of work on strategy, innovation, and organization design. Puranam et al. (2014) for example argue that all forms of organizing consist of unique solutions to the universal problems of task division, task allocation, provision of rewards, and provision of information. Taking these universal problems into account, organizing a firm's pool of human capital in a setting where across-team diversity is a desired attribute would necessitate attention to the host of governance and incentive levers that influence how team boundaries are set, how knowledge flows within and across these boundaries, and how structures for knowledge integration might influence the extent of interactions across teams.

Our primary aim in this paper is thus to be generative with respect to the implications of the across-team diversity concept, and in so doing to demonstrate that it is a relevant dimension of interest for managers concerned with effectively employing the firm's inventive human capital. Yet our theoretical objectives go beyond this; we aim as well to identify the possible mechanisms through which the effects of across team diversity operate. Our starting point for doing so is a stylized fact emerging from the literature on teams (e.g. Bantel and Jackson, 1989; Ancona and Caldwell, 1992; Milliken and Martins, 1996; Williams and O'Reilly, 1998): teams that are diverse face a tension between the learning benefits of different perspectives, and the frictions that must be overcome for these benefits to be realized (Reagans and Zuckerman, 2001).

In the context of firm-level innovation, with the firm's inventive human capital as the key resource, we can reframe this tension as one in which the firm-level manager must balance the innovation benefits of knowledge recombination arising from the diversity of inventors' technical experience with the costs of coordination stemming from the particular ways in which these inventors are configured into teams. A firm's ability to innovate is predicated on the technical experience embodied in its productive human capital (e.g. Grant, 1996; Coff, 1997), with the experience of any individual inventor consisting of that gained over her entire career (i.e., not just at the focal firm). This diversity in inventor technical experience benefits the firm's innovation output because recombination of prior knowledge is a key component of the innovation process (Kogut and Zander, 1992; Hargadon and Sutton, 1997; Fleming, 2001; Katila and Ahuja, 2002; Karim and Kaul, 2015). At the same time, however, coordination costs, arising from interdependencies among inventors, serve as a countervailing force (Thompson, 1967; Lawrence and Lorsch, 1967; Kretschmer and Puranam, 2008; Puranam et al., 2012; Kotha et al., 2013), thereby mitigating the innovative benefits that might arise from such diversity.

Understanding the innovation implications of alternate firm-level diversity regimes then involves weighing the relative impact of knowledge recombination and coordination costs at each organization design level (across- and within-teams). With respect to knowledge recombination, the prior literature points to substantial innovation benefits of spanning boundaries (Rosenkopf and Nerkar, 2001). These benefits arise because spanning (e.g., in our case, team) boundaries helps overcome core rigidities (Leonard-Barton, 1992) and competency traps (Levitt and March, 1988), and enables inventor teams to avoid an inward focus that can reduce innovative output (Stuart and Podolny, 1996). Thus, the productivity of a particular inventor is likely to be shaped by the diversity regime in which she is surrounded. "Boundary spanning" in the context of production teams can involve for example a particular inventor team gaining deeper insight (as a result of its exposure to a diverse set of specialized teams) into how its own knowledge may be applied in alternate settings. Although this might suggest benefits to an across-team diversity regime, since in such a setting the "diverse knowledge" to be recombined is more likely to span team boundaries, it is necessary to weigh this against any associated costs of coordination stemming from such a diversity regime.

The counter-balancing effects of coordination costs arise at two levels. First, there is the need to coordinate among inventors within the team itself; in such a case the inventive process itself necessitates some degree of common ground and joint predictive knowledge that can smooth the ongoing interactions among inventors on a team in order for the team itself to be productive. Second, there is the need to coordinate across multiple teams when knowledge sharing is desirable (e.g., when a given team might benefit from its specialized knowledge being applied in new ways), or when inventions represent modular pieces of a larger effort that must then be reintegrated at a higher level (Kretschmer and Puranam, 2008). Effects at both levels are likely to influence inventor productivity, with the relative ease of coordinating interdependencies within versus across team boundaries a function of factors such as the nature of the knowledge effort being pursued, the extent of the benefits that might arise from sharing information on the use of that knowledge, and the degree of integration necessary at the firm-level.

This discussion suggests that the relative benefits of knowledge recombination as compared to the coordination costs necessary to achieve these benefits under each of the two organizational team design regimes (across- versus within-team diversity) is a question that needs to be adjudicated empirically. Accordingly, in the analyses that follow we examine the average main effects of the two team organization regimes; and then further investigate the possible mechanisms driving these effects, with particular emphasis on how each diversity regime shapes inventor productivity.

3.3 Methods

Our empirical strategy begins by documenting firm-level patterns with respect to the impact of across- and within-team diversity on innovation. In line with our theoretical discussion about the trade-off between knowledge recombination and coordination costs when implementing diversity, we conjecture that many of these effects may arise as a consequence of firm-level diversity regimes affecting the productivity of human capital. First, the firm-level diversity regimes may affect collaboration patterns (team stability) through different coordination costs. Second, the regime may affect the knowledge base that an individual inventor draws upon. To test these explanations for our firm-level results, we reconstruct the data at the inventor-level, and examine the effect of alternative firm-level diversity regimes on the inventors' team stability and breadth of knowledge used.

To study the consequences of team composition for firm-level innovation, we sought an industry with a prevalent use of multiple teams within a firm, where innovation is a key performance metric. The human biotechnology industry fits these requirements well and has several other favorable characteristics for the purpose of this study. First, entrepreneurial firms in an R&D-intensive environment provide a setting in which knowledge-based resources are an important driver of competitive advantage, consistent with our objective of understanding knowledge-based human capital. Scientists and engineers are organized into teams for the purposes of knowledge production, and we can observe this team structure through patent records. Smaller firms with one or few locations also represent a context with managerial flexibility with respect to team design and one in which knowledge sharing across teams may be more feasible (as compared to a multiproduct, multinational setting).[2]

[2] In this study, we primarily document the outcomes of the choice of team structure, although there are a number of remaining questions about the determinants of the team structure itself. We briefly address this in our inventor-level analysis, but further work is needed. The main endogeneity concern is the possibility of an omitted variable that is correlated with both the choice of team structure (the independent variable) and innovation performance (the dependent variable). For example, a superior management team may choose a certain team structure and also be better at generating innovation performance, independent of the team structure. Here, the biotechnology R&D context is also useful since the inventive process is not formulaic, and so managers themselves are unlikely to have a strong ex-ante mapping between team organization and innovation outcomes. We conducted a series of 10 qualitative interviews in the biotechnology industry to understand this phenomenon in more detail. These interviews suggest that there is considerable dispersion of beliefs

In addition, since patenting is key to value appropriation in the biotechnology industry (e.g. Levin et al., 1987), we can be more confident in our reliance on patent data to measure individual- and team-level characteristics within firms (and in particular, team composition structures). While patent data may give rise to issues of generalizability, as we discuss in our final section, it has the benefit of allowing us to observe staffing decisions in a large sample panel set-up, a task that would otherwise be quite difficult.

Finally, we desire as homogeneous a sample as possible, apart from the dimension of team organization, so that we can construct comparable and meaningful measures of innovation. Confining our sample to a single industry setting provides some uniformity in interpreting firm-level objectives; moreover, restricting the sample to venture capital-backed firms further increases the commonality of the likely objectives and time horizon issues facing our sample of firms (thereby reducing the potential for unobserved differences across firms).

3.3.1 Data and Sample

We sample the universe of 476 venture capital-backed human biotechnology (SIC codes 2833—2836) firms founded between 1980 and 2000, as identified using the VentureXpert database. Our primary dataset is an unbalanced firm-year panel in which firms are observed from their year of founding through either 2009 or their year of dissolution. In order to facilitate within-firm inferences (as discussed later, in part through employing specifications with firm fixed effects) a longer time window of observation is desirable. In addition to including all years in which the firm is privately held, we also include in our observation window years post-IPO and post-acquisition of

in staffing production teams, but due to the uncertain nature of the R&D process, there is quite a disconnect between team organization decisions and inventive productivity.

the focal firm by another entity (together with controls for these alternate ownership regimes).[3] We utilize several sources to construct our variables. The IQSS Patent Network database (Li et al., 2014) includes all U.S. Patent and Trademark Office data on patents applied for since 1975 and allows us to uniquely identify inventors associated with patents, and to construct various team measures. Firm-year level attributes come from Deloitte Recap RDNA, Pharmaprojects, Inteleos, ThomsonOne, Zephyr, and various SEC filings.

The inventor-year data are constructed from the same patent data used for the firm-year data. A key empirical design choice for the inventor-level analysis is the assignment of inventor-years to firms, which determines what firm an inventor is employed at in a given year. We consider the first year that an inventor patents at a focal firm to be their first year of employment. An inventor is considered to have left the firm when he patents at a firm that is not the focal firm. We limit that observation window to 5 years after the inventor's first patent at the firm. If we did not have a restricted window, then in cases where the inventor never patents again she would be listed as employed at the focal firm until the end of time, even though she may have departed the focal firm somewhere in that time period. In years where she patents at multiple firms, we attribute her employment to the firm where she has the most patent applications (if there is a tie, we assume she remains at the focal firm). For each inventor identified as employed at a focal firm, we study the five-year window before and the five-year window after the initial time the inventor patents at the focal firm; we interpret this time horizon as the period right before and during her employment at the firm. We also run our analysis on datasets constructed from three and one year pre- and post-employment windows, and find that our main results are

[3]In order to collect patent data on a firm's post-M&A years we follow the procedure outlined in Aggarwal and Hsu (2014), which relies on identifying a firm's pre-acquisition inventors, and matching these to patenting activity by the same inventors in the acquiring firm post-acquisition.

robust to those time window choices.

3.3.2 Firm-Year Level Variables

Dependent Variable

Our main dependent variable is the number of forward citations received within a 4-year post-application window to the firm's patents in the focal firm-year. Forward citations are an accepted measure both of economic value (Trajtenberg, 1990) and of innovative impact (Jaffe and Trajtenberg, 2002). Maintaining a fixed citation window allows us to make meaningful comparisons across observation years; without such a window older patents would be artificially biased upwards in citation count. We also include total (non-citation weighted) patent count as a dependent variable to measure innovation output in order to help us understand whether our results are driven by an effect on innovation impact (forward citations) versus innovation output (patent count).

Independent Variables

Our primary independent variables of theoretical interest are across-team and within-team technical experience diversity. *Within-team diversity* is designed to measure dyadic diversity (in technical experience) among different inventors on a given patent team. We measure the angular distance between the functional experience of every pair of inventors on a team (as described in more detail below), and then average over all pairs of inventors on a team. To aggregate this measure to the firm-level, we then average over all teams in a firm-year (our unit of analysis). *Across-team diversity* is designed to measure how patent teams differ from one another (in terms of technical experience) on a pairwise (dyadic) basis. To construct this variable we first measure the distance between the functional experience of every pair of patent teams, and then average over all such pairs.[4]

We measure the diversity between any pair of inventors using a cosine similarity measure, also known as angular distance, or angular separation (Jaffe, 1986). For each inventor at each year of her career, we define a class experience vector representing the total experience the inventor has had patenting in each technology class, both in her current firm and in all prior firms; each entry of the vector represents a stock count of the inventor's patents in that particular technological class up to the focal year, and the dimension of the vector is the total number of primary patent classes used by the USPTO. Cosine similarity is defined as the angular separation between these class experience vectors of the two inventors (Jaffe, 1986), while cosine diversity is defined as 1 minus the cosine similarity of the two inventors. The diversity measure thus ranges from 0 to 1, where 1 is completely diverse (no technological overlap) and 0 is completely homogeneous (full technological overlap).

To construct the *within-team diversity* measure, for a given team of inventors on a patent—referred to as a patent team—we form all possible dyads between the inventors, and then calculate the cosine diversity for each dyad. For each patent, we average cosine diversity over the set of all inventor dyads, forming a diversity measure for each patent. We then average over all patents in a firm-year to form a firm-year measure.

To construct the *across-team diversity* measure, we sum the class experience vectors of the inventors on a patent team (i.e., the set of inventors on a given patent) and create a single class experience vector for the entire patent team. We then take

[4]We organize our empirical analyses with these two forms of diversity treated as independent constructs. In unreported results we find that our theoretical predictions are robust to the inclusion of the interaction effect among the two constructs. We also find that the interaction is not significant in our model specifications; we thus choose to report the more concise model specification (i.e., without the interaction), as this specification concords more closely to our theoretical framework.

the set of patents in a firm-year and form all possible dyads between each patent. For each dyad, we calculate the cosine diversity measure as before, but instead using class experience vectors for the entire patent team with the final measure then constructed as an average over all dyads of patent teams in a firm-year. Figure 3.2 gives a detailed example of how we calculate the across-team and within-team diversity measures.

——————Insert Figure 3.2——————

Control Variables

We employ a set of time-varying controls, each measured at the firm-year level, in order to account for any residual unobserved heterogeneity beyond the time invariant firm-level characteristics we control for with firm fixed effects (which are included in all specifications). There are three categories of controls: inventor team controls; firm patenting controls; and corporate (firm-level) controls. We discuss the rationale for each category of controls in turn.

The "inventor team controls" account for the technological experience embodied in the firm's inventors, measured as an aggregate total at the individual team level, and then averaged across teams in the firm-year. Inventor experience includes not only that gained by inventors within the context of the firm itself, but also that which the firms' inventors have gained over the course of their entire careers. We include the following variables: *team patenting experience*, which measures the collective number of patents held by inventors on the firm's patent teams; *team forward citation experience*, which similarly measures the collective number of forward citations of the inventors on a team; and *team class experience*, which measures the unique number of patent classes represented by inventors on a team. All measures are averaged across the firm's patent teams in a given firm-year. Employing this set of controls thus broadly accounts for the overall experience level of the firm's inventors.

The "firm patenting controls" measure characteristics of the firm's overall portfolio of inventors and experience. In conjunction with the slate of "corporate controls" described next, this set of variables accounts for various time-varying dimensions of firm scale, scope, and quality, all of which may be correlated with both team design characteristics and innovation output. The firm patenting controls include *patent count*, which is the total number of patents applied for by the firm in the firm-year; *inventor count*, which is the unique number of inventors in the firm-year; and *class span*, which is the unique number of classes in which the firm patents in the firm-year.

Finally, the "corporate controls" further account for a set of time-varying characteristics that could correlate with team design and innovation. Collectively these variables measure various characteristics of firm quality and development stage that are relevant in our industry setting of early-stage venture capital-backed biotechnology firms. These controls include the *age* of the firm; *VC inflows stock*, which measures cumulative venture capital investment into the firm (from VentureXpert); *strategic alliance stock*, which measures the cumulative stock of the alliances in which the firm has been involved to date (from Deloitte Recap RDNA); and *active product (all stages)*, which is an indicator for whether the firm has at least one active product in the Food and Drug Administration (FDA) pipeline (from PharmaProjects and Inteleos). We also control for the firm's ownership using the *post-IPO* and *post-M&A* variables (privately-held is the baseline), as the ownership regime of the firm is likely to influence both team organization and innovation (these variables are hand-collected using archival news sources). *Post-IPO* indicates that the firm has undergone an initial public offering (IPO) in or before the focal year, and *post-M&A* is an indicator that the firm has undergone a merger or been acquired in or before the focal year. Table 3.1 provides definitions and summary statistics, while Table 3.2 provides pair-wise correlations of our independent variables.

———————Insert Table 3.1———————

———————Insert Table 3.2———————

3.3.3 Inventor-Year Level Variables

We construct a number of patent-based measures to test the effect of diverse across-team and within-team regimes on an inventor's collaboration patterns. The variables in the difference-in-differences design are derived from the previously described firm-level measures of across-team diversity and within-team diversity, which represent two distinct effects. We define the "treatment" groups as inventors who in their observed five year employment window at a focal firm ever enter an above-median level (relative to the full sample of observed values) of across-team or within-team diversity. If they do, then *high across-team diversity* or *high within-team diversity* take a value of 1 respectively (and it would remain 0 if they never enter the respective regime). The main variables of interest, *high across-team diversity * post across-team entry* and *high within-team diversity * post within-team entry* take a value of 1 in the years after and including the first year that the inventor is employed at the focal firm and the focal firm is in an above median diversity regime, and 0 otherwise.

The "treatment" groups are defined as whether or not the inventor crosses the threshold for the median level of across-team or within-team diversity observed in our sample. Across-team and within-team diversity are considered separate "treatments". The post period is thus the period after they cross into the above median level of (either form of) diversity.

We construct a set of dependent variables to measure both the collaboration patterns (team stability) and breadth of knowledge drawn upon by the inventor. Collaboration patterns are measured through the focal inventor's co-patenting history. *Inventor existing collaborators* is a count of unique inventors patenting with the focal inventor in the focal year with whom the focal inventor had patented in the past. A stable pattern of collaborations, where existing collaborators are preserved, can be thought of as evidence of team stability. *Inventor new collaborators* is the count of inventors that the focal inventor patented with in the focal year that the inventor had never patented with before. We measure the breadth of knowledge used by the inventor by looking at her backward citation history. *Inventor originality* is the average originality over the of the inventor's set of patents in the focal year. Originality is a patent-level Herfindahl-based measure of the breadth of the technological origins of the patent (Trajtenberg et al., 1997): an originality value of 0 means the patent only cites one technological class, while an originality value approaching 1 means that the patent cites many technological classes. *Inventor firm self citations* is a count of backward citations which are assigned to the employing firm, but where the focal inventor was not an inventor.

For controls, we include *inventor patent count*, the total count of the inventor's patents up to the focal year, *inventor forward citations (4Y)*, the forward citations made to the inventor's stock of patents within a 4-year window following the application date of the respective patents, *inventor class experience*, the count of classes spanned by the stock of the inventor's patents up to the focal year, and *inventor career length*, the time in years between the inventor's first patent and the focal year. Table 3.4 provides summary statistics for the inventor-year level data.

3.3.4 Model Specifications

We employ conditional fixed effects Poisson models with robust standard errors in our main analyses at the firm-year level. This estimation technique is appropriate because our dependent variables, *forward citations (4Y)* and *patent count*, are non-negative counts (Hausman et al., 1984; Hall and Ziedonis, 2001). We employ firm and year fixed effects throughout in order to control for time-invariant firm qualities and year-to-year changes that might correlate with both production team organization and firm innovation. Together with the set of controls described above, the conditional firm fixed effects specification facilitates the interpretation of our results as estimating within firm, across time effects.

We implement a difference-in-differences design for the analysis of our inventor-year data. We run ordinary least squares (OLS) regressions with robust standard errors instead of a non-linear model to simplify the interpretation of the coefficients in the empirical specification. Since we have two "treatments," we define two different treatment groups, included simultaneously in the models. We include firm dummies to control for both firm average effects, as well as to control for the pure act of entry into a firm. These are distinct from firm fixed effects since they take a value of 0 in the years before an inventor joins a focal firm. The inclusion of year fixed effects eliminates the need to include variables indicating the post time period after the inventor has entered either regime, since they are collinear. A statistical and visual check of the inventor-level outcomes before they enter either regime finds that the pre-trend is statistically indistinguishable, and suggests that the difference-in-differences analysis is valid.

3.4 Results

Table 3.3 reports the specifications we use to test our main effects. The reported coefficients are incidence rate ratios—i.e., the exponentiated Poisson regression coefficients. The interpretation of these coefficients is as follows: for a unit increase in an independent variable, the incidence rate of the dependent variable would be expected to be scaled (multiplied) by the value of the coefficient on that independent variable. Thus, a coefficient value less than one should be interpreted as a negative effect, while a coefficient value greater than one should be interpreted as a positive effect. In both the written description and the tables we present p-values in lieu of standard errors, and omit the usual presentation of "stars" indicating thresholds of statistical significance per the new guidance proposed by Bettis et al. (2015).[5]

3.4.1 Firm-Year Level Analysis

We report the results of the across-team and within-team diversity effects in Table 3.3; the first three specifications have a dependent variable of forward citations within a four-year window on patents applied for in the focal year, and the last specification (3-4) has the count of patents applied for in the focal year as the dependent variable. Specification (3-1) reports just the across-team and within-team results, (3-2) adds team patenting controls, and (3-3) includes the remainder of our firm-level controls.[6] We use Poisson specifications with both firm and year fixed effects (and robust standard errors) in all models, and run the analyses at the firm-year level. We see that there is a positive effect on *across-team diversity* and a negative effect on *within-team diversity* (recall that the coefficients are incidence rate ratios), results which are consistent across the three specifications, and all of which are significant at a p-value of 0.1%. The results suggest that shifting the across-team structure of a firm from complete functional experience homogeneity (0) to fully diverse (1) yields 103.3% more forward citations in the most parsimonious specification (3-1) to

[5]Following Bettis et al. (2015), we choose to report p-values in the table, which are based on robust standard errors. Tables with the associated robust standard errors reported (instead of p-values) are available upon request.

[6]We also find (in unreported regressions) that our results are robust to including various combinations of the firm patenting controls of *patent count*, *inventor count*, and *class span*.

70.6% more forward citations in the full specification (3-3). Going from complete within-team functional homogeneity (0) to full within-team diversity (1) results in approximately 50% fewer forward citations in specifications (3-1), (3-2), and (3-3), with significant p-values of 6%, 0.7%, and 3.5% respectively. We perform a Wald test on the equality of the coefficients for *across-team* and *within-team diversity* in each of the three specifications and can reject the null that the coefficients are equal with a p-value of less than 0.1%. In the analysis where patent count is the dependent variable, specification (3-4), and we find that the across-team diversity coefficient has less statistical significance, with a p-value of 16.5%, but the within-team diversity coefficient is negative with a p-value of less than 0.1%; going from complete within-team functional homogeneity (0) to full within-team diversity (1) is associated with 63.1% less patenting. We find that the statistical significance of our main independent variables with respect to their influence on innovation impact (as measured by forward citations) is higher than it is with respect to general innovation output (as measured by patent count).

——————**Insert Table 3.3**——————

3.4.2 Inventor-Year Level Analysis

We turn to the inventor-year level analyses in Table 3.4 and Table 3.5. Table 3.4 provides summary statistics and variable definitions, while Table 3.5 presents the results of the inventor-year difference-in-differences analysis.[7] We find a positive coefficient on the "treatment" of across-team diversity for the outcome variable *inventor current existing collaborators* (5-1) but not for *inventor current new collaborators* (5-2), with p-values of less than 0.1% and of 6.7% respectively. The entry of an inventor

[7]We also run models with an interaction effect of the two different "treatments," but find that the interaction term coefficient is not significant.

into a regime of high across-team diversity is associated with 0.19 more collaborations with inventors with whom she worked previously. These results suggest some dimension of team stability (a correlate of coordination costs): in a high across-team regime, inventors are likely to keep working with inventors they worked with in the past, but not with new inventors they have not worked with before. We find a relatively small positive effect size on the treatment of within-team diversity for inventor current existing collaborators (5-1), with a p-value of 1.3%, but a relatively large negative coefficient for inventor current new collaborators (5-2) with a p-value of less than 0.1%. The entry of an inventor into a regime of high within-team diversity is associated with .08 more collaborations with inventors with whom she worked previously but 0.14 fewer collaborations with inventors with whom she never worked with before: combining the two results, a high within-team diversity regime is thus associated with less net collaboration. A Wald test on the difference between the coefficients for the main independent variables for entry into either the high across- or high within-team regime is statistically significant with p-values of 3.4% and 1.4% in specifications (5-1) and (5-2) respectively. These distinct findings suggest that across-team and within-team diversity do have distinct effects at the inventor-level, which may drive the firm-level findings discussed earlier.

We find negative coefficients on both "treatments" with regard to firm self-citations (5-3) and originality (5-4) and of their patents. In specification (5-3), entry into a high across-team or high within-team regime is associated with 0.10 or 0.12 fewer self-citations back to the focal firm respectively; a Wald test shows that the difference between these two coefficients is statistically insignificant (with a p-value of 82.7%). In both dimensions of diversity, inventors draw less from knowledge within the firm and more from knowledge external to it, suggesting that either diversity regime reduces exploratory behavior with respect to knowledge outside firm boundaries. This negative effect may not necessarily have a negative performance impact on firm-level innovation, and may be indicative of a lower need for individual inventors to gather knowledge from outside the firm. The originality coefficients presented in (5-4) imply that in diverse regimes on either dimension, inventors draw from a less diverse base of knowledge to form their inventions, with 0.046 and 0.073 lower levels of originality for across-team and within-team diverse regimes, which is equivalent to 0.12 and 0.20 standard deviations of the originality values.[8] A Wald test shows that the difference between coefficients for the main independent variables for entry into either a high across- or a high within-team regime is statistically significant with a p-value of 0.1%. Given the consistent results across distinct dependent variables of originality and firm self-citations, which are proxies for knowledge recombination or exploratory behavior, we can infer that the two diversity regimes do not have a substantially distinct effect, and are ambiguous with regard to the effect on knowledge recombination.

Insert Table 3.4

Insert Table 3.5

3.5 Discussion

In this study we examine the link between the organization of inventive human capital within a firm and the firm's innovation output. We introduce the notion of across-team diversity, exploring the idea that alternate ways of organizing a firm's inventors' prior technical experience influences innovation via the mechanisms of knowledge recombination and coordination costs. Using the empirical context of biotechnology

[8] We ran the same analysis for other dependent variables which are proxies for breadth of knowledge base used: complexity (Fleming, 2001; Fleming and Sorenson, 2001) and backward citation class span. The results are robust to the choice of dependent variable.

start-ups, we find that at the firm-level, across-team technical experience diversity results in greater benefits to firm-level innovation output as compared to within-team technical experience diversity. We examine how these two alternate regimes shape the productive output of a firm's human capital, finding that the main lever distinguishing the impact of alternate technical experience diversity regimes is team stability, a proxy for coordination costs.

Before turning to the implications of our results for theory and future research, we briefly touch on several limitations of the present study. First, our use of patent data as a measure of innovation raises the issue of generalizability. The use of patenting varies significantly across industries; while in biotechnology, medical instruments, and pharmaceuticals, patents have been effective at protecting intellectual property arising from R&D (Arora et al., 2008b), this holds to a lesser degree in other industries such as software (Bessen and Maskin, 2009). Relatedly, patent data only capture "patentable" innovations disclosed by the firm, and not innovations retained as trade secrets, or otherwise unpatented. Future work might thus examine the degree to which our findings hold in other industries where patents are less salient as a measure of innovation. Second, our empirical strategy is to infer team composition from the list of inventors on a patent; we might be concerned, however, about other features of team composition that might be salient. As an example, it is not obvious from the data whether teams are co-located or not. Finally, although we have focused on the association between team organization and innovative performance, how team structure itself is set is an area for further exploration. We partially address this via our inventor-level analysis in which we explore the collaboration patterns of inventors, but future work might seek to address this issue directly.

Our work has implications for several research streams within the strategy field, including work in the domains of organization design, strategic human capital, and teams. With respect to the literature on organization design, the technical experience diversity constructs we develop in this paper have implications for how we might conceptualize several of the core issues in that body of work. As noted previously, organization design involves a set of fundamental choices that include task division, task allocation, provision of awards, and provision of information (Puranam et al., 2014). To the degree that across-team diversity has a beneficial influence on innovation as a result of enabling greater team stability, future work might then address the various organization design contingencies that can influence this effect. For example, in a within-team diversity setting, can factors such as the provision of information and awards be structured so as to achieve the benefits of team stability? More generally, our finding that across-team diversity is influential with respect to a firm's innovation output suggests that the particular role it plays should be taken into account when a firm manager considers employing levers such as inter-team governance and employee incentive systems.

Future research in the domain of organization design might examine issues such as the determinants of heterogeneity in across- and within-team diversity (i.e., the drivers of alternate firm-level technical experience diversity regimes in the first place); the nature of interdependencies across-teams; and the micro-foundations of interdependencies in an across-team setting, with a particular view on how these interdependencies differ from those which exist within a particular team. There is a growing literature on coordination mechanisms, which are necessary to address interdependencies, which can take the form of ongoing communication, modularity, and tacit coordination mechanisms (Srikanth and Puranam, 2014). On the within-team coordination dimension, ongoing communication and tacit coordination mechanisms are likely to be present. While the across-team dimension represents a modularity choice by the firm, there may be ongoing communication and tacit coordination across-teams as well. Further work should explore the use of coordination mechanisms both within- and across-teams.

A second domain of work relevant to our study is the literature on strategic human capital. This literature views firm-specific human capital as a source of competitive advantage (e.g. Campbell et al., 2012), and tends to stress employee inter-organizational mobility. Our study points to an important additional dimension through which firms can create value from their human capital assets: via the re-organization of internal labor resources, as alternate regimes of technical experience diversity can influence the effectiveness with which a firm's labor is utilized.

Future research in strategic human capital incorporating the findings presented here may explore a variety of directions. A first such avenue relates to how the alternate dimensions of team organization influence the balance between firms' use of the internal versus external labor markets. Internal labor markets are a major source of human capital (especially) when there are frictions to hiring externally. We find that organization regimes affect team stability and the ability to retain labor within teams, and this same mechanism could affect the ability of firms to retain labor within firm boundaries (though that we leave for future investigation). Second, while we study one particular human capital attribute (inventive ability), the notion of across-team diversity may be conceptualized across a host of other relevant human capital attributes. Future work might thus aim to understand not only the implications of the organization of each such attribute in isolation, but also with respect to the interactions of these attributes with one another. Third, as the literature suggests, managers are imperfect in their measurement of human capital in the sense that they undervalue general human capital and overvalue firm-specific human capital (Campbell et al., 2012). Does this bias influence the ability of managers to effectively allocate human capital across teams? And how does this bias relate to our construct of team stability? What implications do imperfections in workers' own assessments of their attributes have for team composition (and the resulting innovation and performance implications associated with team organization)?

Finally, with respect to the strategy literature more generally, while there has been a large body of work examining top management teams (TMTs), work on production teams has been relatively scarce. We hope that this study might ignite interest among scholars in addressing this unit of analysis, with a particular focus on the notion of across-team diversity as a construct of interest. For example, given that firms contain multiple production teams, how do the findings regarding factors such as age and tenure (Ndofor et al., 2011), functional experience (Eesley et al., 2014; Qian et al., 2013), and nationality (Nielsen and Nielsen, 2013) operate in an across-team framework? For founding teams in an entrepreneurial context, who themselves may be situated within a broader setting (e.g., an accelerator or ecosystem), we might conceptualize these teams as being a part of a community of teams; do across-team effects apply when there is also a firm boundary around the team?

In conclusion, by focusing on the impact of the organization of inventive human capital within a firm, this study opens a number of avenues for future work in the domain of strategy related to organization design, strategic human capital, and teams.

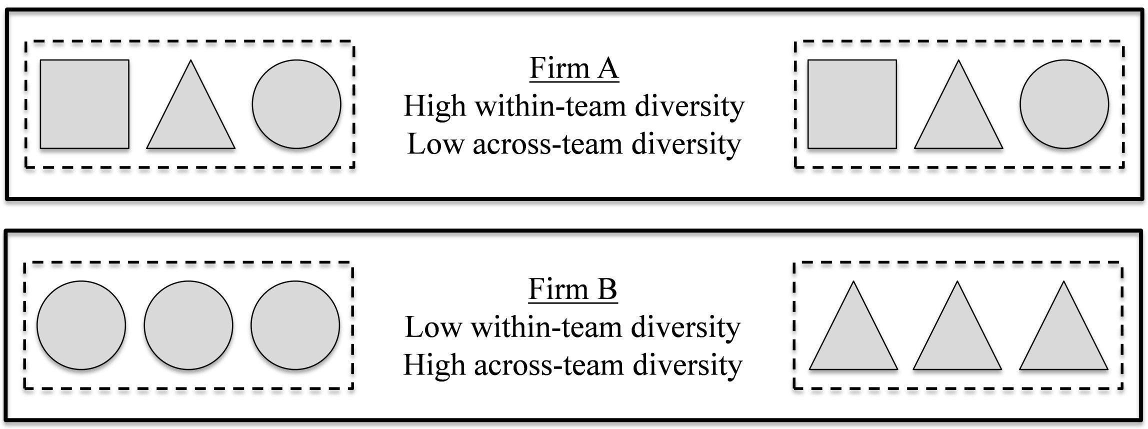

Figure 3.1: **Across-Team and Within-Team Diversity**. This figure depicts two alternate firm-level approaches to organizing inventors on teams within a firm. *Firm A* is a firm with high within-team diversity and low across-team diversity, and *Firm B* is a firm low within-team diversity and high across-team diversity. The dashed lines represent team boundaries, and solid lines represent firm boundaries. The shapes represent particular types of inventors on a team.

	Count of Patents in Each Class						
	Team 1					Team 2	Team 3
Class	John	Paul	George	Ringo	Total	Total	Total
1	3	3	0	3	9	4	0
2	4	4	0	0	8	3	6
3	0	0	5	4	9	0	2

Within-Team Diversity of Team 1		Across-Team Diversity of Firm	
Pairings	Dyadic Diversity $1-\frac{A \cdot B}{\|A\| * \|B\|}$	Pairings	Dyadic Diversity $1-\frac{A \cdot B}{\|A\| * \|B\|}$
John & Paul	0	Team 1 & Team 2	$1-\frac{12}{\sqrt{226}}$
John & George	1		
John & Ringo	16/25	Team 2 & Team 3	$1-\frac{9}{5\sqrt{10}}$
Paul & George	1		
Paul & Ringo	16/25	Team 3 & Team 1	$1-\frac{33}{2\sqrt{565}}$
George & Ringo	1/5		
Within-Team Diversity	0.58	Across-Team Diversity	0.31

Figure 3.2: **Calculation of Diversity Measures**. This figure demonstrates the process for calculating the across-team diversity and within-team diversity measures used in the empirical analysis for a hypothetical firm. The table at the top shows the stock count of patents in each primary patent class for the members of *Team 1*, and the total amounts for *Team 2* and *Team 3*. The lower left table shows the calculation for the within-team diversity of *Team 1*, where the dyadic diversity, which is 1 minus the cosine similarity of each dyad, is calculated for each dyad of inventors, and then averaged across all dyads. The lower right table shows the calculation of across-team diversity for the firm, where dyadic diversity is calculated for each dyad of teams and then averaged across all dyads.

Table 3.1: **Summary Statistics for Firm-Year Analysis**. This table presents the summary statistics and variable definitions for the firm-year level of analysis in Table 3.3. Correlation coefficients are presented in Table 3.2.

Variable	Definition	Mean	S.D.
Dependent Variable			
Forward Citations (4Y)	Total forward citations within a four-year window to granted patents filed in firm-year	5.14	21.46
Main Independent Variables			
(1) Across-Team Diversity	Average angular distance in technology class experience between patent teams	0.12	0.23
(2) Within-Team Diversity	Average angular distance in technology class experience between inventors on a patent team, averaged over teams	0.20	0.18
Inventor Team Controls			
(3) Team Patenting Experience	Average patenting experience of teams in a firm	9.81	10.72
(4) Team Fwd. Citation Experience	Average forward citations within a four-year window to patents by teams in a firm	29.18	70.28
(5) Team Class Experience	Average class experience of teams in a firm	4.70	3.30
Firm Patenting Controls			
(6) Patent Count	Number of patents in a firm-year	2.24	7.93
(7) Inventor Count	Number of inventors in a firm-year	4.46	12.61
(8) Class Span	Number of classes in a firm-year	0.80	1.47
Corporate Controls			
(9) Age	Years since firm founding	8.42	6.09
(10) VC Inflows Stock	Cumulative venture capital investment into the firm	16.39	27.88
(11) Strategic Alliance Stock	Stock count of strategic alliances	10.39	17.91
(12) Active Product (All Stages)	Indicator for an active product under FDA review	0.65	0.48
(13) Post-IPO	Indicator for IPO in firm history	0.32	0.47
(14) Post-M&A	Indicator for M&A in firm history	0.15	0.35

Table 3.2: **Correlation Matrix for Firm-Year Analysis**. This table presents the pairwise correlation matrix of independent variables for the firm-year level of analysis. The labels across the top and on the left on side correspond with Table 3.1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
(1)	1													
(2)	0.05	1												
(3)	-0.03	0.07	1											
(4)	-0.05	0.03	0.57	1										
(5)	0.04	0.37	0.53	0.25	1									
(6)	0.20	-0.04	0.36	0.14	0.10	1								
(7)	0.30	-0.02	0.19	0.04	0.16	0.77	1							
(8)	0.45	0.03	0.25	0.11	0.19	0.71	0.79	1						
(9)	0.02	-0.10	0.11	-0.02	0.10	0.08	0.15	0.09	1					
(10)	0.07	0.03	0.16	0.00	0.23	0.09	0.14	0.20	0.11	1				
(11)	0.21	-0.05	0.15	-0.01	0.11	0.31	0.46	0.40	0.43	0.15	1			
(12)	0.05	-0.11	-0.11	-0.11	-0.14	0.04	0.07	0.06	0.34	-0.14	0.14	1		
(13)	0.15	-0.04	0.09	-0.05	0.10	0.19	0.24	0.30	0.39	0.21	0.45	0.27	1	
(14)	-0.03	-0.03	0.03	0.00	-0.03	-0.06	-0.06	-0.09	0.30	0.06	0.07	-0.09	0.15	1

Table 3.3: **Average Effects for Firm-Year Analysis**. This table presents the average effects of across-team and within-team diversity at the firm-year level of analysis. Specifications (3-1), (3-2), and (3-3) use firm forward citations over a four year window as the dependent variable, and specification (3-4) uses firm patent count as the dependent variable. All specifications are estimated using conditional firm fixed effects Poisson estimation with robust standard errors. Reported coefficients are incidence rate ratios, and p-values are reported in parentheses. Following the guidance of Bettis et al. (2015), we report coefficients as well as actual p-values (calculated based on robust standard errors) in parentheses. Values for the robust standard errors are available upon request.

	Forward Citations (4Y)			Patent Count
	(3-1)	(3-2)	(3-3)	(3-4)
Across-Team Diversity	2.033	1.907	1.706	1.203
	(0.000)	(0.000)	(0.001)	(0.165)
Within-Team Diversity	0.515	0.475	0.527	0.369
	(0.060)	(0.007)	(0.035)	(0.000)
Team Patenting Experience		1.007	0.992	1.013
		(0.192)	(0.265)	(0.000)
Team Fwd. Citation Experience		1.000	1.002	0.999
		(0.729)	(0.156)	(0.313)
Team Class Experience		1.055	1.049	1.003
		(0.002)	(0.009)	(0.741)
Patent Count			1.007	
			(0.000)	
Inventor Count			0.998	1.003
			(0.539)	(0.003)
Class Span			1.089	1.116
			(0.026)	(0.017)
Age			1.469	1.156
			(0.323)	(0.384)
VC Inflows Stock			1.001	1.001
			(0.824)	(0.679)
Strategic Alliance Stock			1.010	1.000
			(0.004)	(0.936)
Active Product (All Stages)			1.087	1.062
			(0.582)	(0.599)
Post-IPO			0.994	1.187
			(0.964)	(0.073)
Post-M&A			0.679	0.702
			(0.019)	(0.004)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Log Pseudo-likelihood	-19855.1	-14824.3	-12004.1	-4428.7
Observations	4386	2546	2283	2314

Table 3.4: **Summary Statistics for Inventor-Year Level of Analysis**. This table presents the summary statistics and variable definitions for the inventor-year level of analysis in Table 3.5.

Variable	Definition	Mean	S.D.
Dependent Variables			
Inventor Existing Collaborators	Number of co-inventors with whom the inventor patented previously	0.86	2.47
Inventor New Collaborators	Number of new co-inventors	0.97	2.75
Inventor Originality	Originality of inventor's patents	0.23	0.36
Inventor Firm Self Citations	Backward citations to the inventor's employer	0.36	2.27
Independent Variables			
High Across-Team Div. * Post Across-Team Entry	Indicator when inventor enters a firm-level regime of high across-team diversity	0.50	0.50
High Within-Team Div. * Post Within-Team Entry	Indicator when inventor enters a firm-level regime of high within-team diversity	0.51	0.50
High Across-Team Div.	Indicator if the inventor ever enters a firm-level regime of high across-team diversity	0.70	0.46
High Within-Team Div.	Indicator if the inventor ever enters a firm-level regime of high within-team diversity	0.76	0.43
Inventor Controls			
Inventor Patent Count	Cumulative patents by the inventor	4.47	9.13
Inventor Fwd. Cit. (4Y)	Forward citations within a four year window of cumulative patents by the inventor	6.90	23.40
Inventor Class Experience	Number of classes spanned by cumulative patents by the inventor	1.77	1.91
Inventor Career Length	Years between the inventor's first patent and the focal year	4.81	5.56

Table 3.5: **Average Effects for Inventor-Year Level of Analysis**. This table presents the average effects of across-team and within-team diversity in a differences-in-differences specification at the inventor-year level. All specifications are estimated using ordinary least squares (OLS) with firm fixed effects and robust standard errors. Reported coefficients are directly from OLS, and p-values are reported in parentheses. Following the guidance of Bettis et al. (2015), we report coefficients as well as actual p-values (calculated based on robust standard errors) in parentheses. Values for the robust standard errors are available upon request.

	Inventor Existing Collaborators	**Inventor New Collaborators**	**Inventor Firm Self Citations**	**Inventor Originality**
	(5-1)	**(5-2)**	**(5-3)**	**(5-4)**
High Across-Team Div.	0.186	0.017	-0.104	-0.046
* Post Across-Team Entry	(0.000)	(0.668)	(0.003)	(0.000)
High Across-Team Div.	0.033	0.091	0.094	0.039
	(0.218)	(0.006)	(0.000)	(0.000)
High Within-Team Div.	0.079	-0.139	-0.117	-0.073
* Post Within-Team Entry	(0.013)	(0.000)	(0.001)	(0.000)
High Within-Team Div.	0.035	0.181	0.151	0.063
	(0.222)	(0.000)	(0.000)	(0.000)
Inventor Patent Count	-0.007	-0.002	0.001	0.003
	(0.000)	(0.274)	(0.528)	(0.000)
Inventor Fwd. Cit. (4Y)	0.001	-0.001	0.006	0.001
	(0.001)	(0.001)	(0.000)	(0.000)
Inventor Class Experience	0.063	-0.005	-0.003	0.004
	(0.000)	(0.465)	(0.632)	(0.003)
Inventor Career Length	-0.008	-0.030	-0.007	-0.006
	(0.000)	(0.000)	(0.000)	(0.000)
Firm Dummies	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-Squared	0.0282	0.0161	0.123	0.0838
Observations	75757	75757	75757	75757

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