Distribution Agreement

Ananya Chatterjee as of November 1, 2023

Title Social Similarity and Structural Positioning in Venture Capital

Author Ananya Chatterjee

Degree Master of Science

Program Business

Approved by the Committee

Ozgecan Kocak
Advisor

Demetrius Lewis
Advisor

Committee Member

Committee Member

Committee Member

Committee Member

Accepted by the Laney Graduate School:

Kimberly Jacob Arriola, Ph.D, MPH
Dean, James T. Laney Graduate School

Date

Social Similarity and Structural Positioning in Venture Capital

Ananya Chatterjee

Bachelor of Science in Economics, University of Pennsylvania
Master of Arts, University of Chicago

An abstract of
A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of Master of
Business Studies
2023

Abstract

Venture capital is an idiosyncratic asset class. The seemingly endless number of different deal types and players involved makes it difficult to unpack firm performance. The literature underscores many tensions that firms in this space must confront when grappling with internal constraints. Many of these revolve around the role of knowledge similarity on performance. I focus on the level of knowledge matching between a venture capital deal team and its startup investment. I measure profitability outcomes among all firms in the dataset and find that at the later stages of a startup's development, similarity in knowledge matching is less important than working with an investor with the skills needed to help the startup grow. I also examine the importance of network structure, which is related to arguments about knowledge similarity. One is about existing information capabilities, and the second is about the flow of that information within the organization. My findings indicate that a high number of structural holes and a high network range, or in other words, a wider distance of knowledge spanned in the network, are helpful for performance. The combined effect of high structural holes and high levels of knowledge matching is what produces favorable funding outcomes, suggesting that venture capital firms and startups should think carefully about how to partner with one another given each other's organizational structures. The knowledge held within an organization's employees is one of its biggest assets and should not be ignored. Given the ultimate goal of working better together to foster growth, firms can manage their resources, whether knowledge or network structure, for stronger competitive performance and growth.

Keywords— firm performance, venture capital, brokerage, structural holes, knowledge

I am grateful to my dissertation committee members for their time, patience, guidance, and encouragement. In addition, I thank the entire Organization & Management department for their helpful comments and continued support. Finally, thank you to the Goizueta Business School and the Sheth Family Fellowship for their financial support during my studies.

Social Similarity and Structural Positioning in Venture Capital

Ananya Chatterjee

Bachelor of Science in Economics, University of Pennsylvania
Master of Arts, University of Chicago

A thesis submitted to the Faculty of the
James T. Laney School of Graduate Studies of Emory University
in partial fulfillment of the requirements for the degree of Master of Business Studies
2023

Contents

1 The Role of Human Capital

In venture capital, a rich literature describes how the social capital of investors, derived from relationships with co-investors, entrepreneurs, and other stakeholders, enhances successful portfolio management (Bygrave, 1987; Dimov and Milanov, 2010; Sorenson and Stuart, 2001; Ter Wal et al., 2016a). However, the role of social similarity and its role in performance is underexplored. In this essay, I address this gap to discuss how social similarity influences financial performance. I broadly examine how firms can adapt their investment strategies, depending on their internal firm capabilities, to improve returns. To do this, I analyze venture capital investments and investment performance from 1990-2018.

This study aims to contribute to the venture capital literature an understanding of how differences in firm performance can be explained by social similarity, especially at different stages of a firm's development.

1.1 Theory

There is a strong tendency to gravitate towards those similar to us. Many authors focus on the consequences of this behavior and ask how our peers and background affect our success (Åstebro et al., 2012; Ertug et al., 2022; Falck et al., 2012; Lerner and Malmendier, 2013; Nanda and Sørensen, 2010). While theoretical logic and evidence illustrate how social similarity makes it easier for people to access the tools they need to generate better outcomes (Argote et al., 2003; McPherson et al., 2001; Ertug et al., 2022), too much overlap in the information they have access to could be detrimental to performance. These two ideas are in conflict, but this does not have to be the case. One under-explored possibility is that both could be true at different times, depending on the needs of the organization in question at each stage of development.

The literature on organizational inertia (Hennart et al., 1998) has focused on changes in entry and exit decisions, but not on changes in an organization's underlying network structures (Kim et al., 2006). One line of thinking is that due to the embedded nature of interorganizational networks (Granovetter, 1973; Uzzi, 1996) and the effect of relationship-based routines, firms are slow to replace them (Kim et al., 2006). However, this may not be the case if we look over a long period of time or within organizations that pride themselves on constant change.

It has long been known that the main goal of new startups is to achieve financial success (Ruhnka and Young, 1987; Song et al., 2008). Part of that success is driven by factors internal to the firm, but part depends on the other firms with whom they partner. Specifically, I want to examine the relationship between a startup and its venture capital ("VC") investor. While established firms can draw upon the knowledge necessary to initially generate high returns (Kogut and Zander, 1992), new startups tend to lack the requisite capabilities to accomplish this (Hashai and Zahra, 2021). They choose to partner with VCs, who provide investments with capital, connections, knowledge, and other resources in hopes of a lucrative exit (Gorman and Sahlman, 1989; Hsu, 2004a). VC investing teams are crucial to the growth of their startup investments, and startup executives will pay high premiums for investments from experienced VCs with strong experience and networks in the investing space (Hsu, 2004a). Startup executives want to find VC investors who can refine their capabilities and maximize performance at exit. Given how much time VCs devote to helping young startup portfolio companies establish themselves (Gorman and Sahlman, 1989) and ultimately generate outsized returns, the influence of a close VC partner will be significant. This is especially true considering a core part of a VC's role is "obtaining external resources when the assets of their start-up are intangible and knowledge-based" (Hsu, 2004a, p. 1805).

Both early and late-stage startups share this same goal of financial success, but their paths to achieve this are not the same; one is much closer to the finish line than the other. Early-stage startups need to first coalesce as a team (Chang, 2004), which they can achieve in several ways.

Prior literature tells us that startups managed by those with aligned knowledge tend to perform better (Hashai and Zahra, 2021) because they share prior routines (Simsek et al., 2015). This similarity allows them to build trust and communicate more often, which are needed for successful coordination (Eisenhardt and Schoonhoven, 1990). Coordinating smoothly and running their startup more effectively results in better performance (Agarwal et al., 2004; Beckman, 2006). Considering that those at early-stage startups are still building cohesive teams, they will want to partner with a VC that can complement that knowledge. I expect that knowledge similarity will yield better funding outcomes—more capital—which is what early-stage startups need to grow (Nanda and Rhodes-Kropf, 2013). For these reasons, startups choose to work with VC investors with knowledge that strengthens their own.

Hypothesis 1: In the early stage of their development with regards to profitability, startups perform better if they share high knowledge similarity with their VC investor

On the other hand, late-stage startups already have formed cohesive initial teams and instead want to focus on accelerating their growth enough to exit. The executives at late-stage startups have built some degree of trust internally within the team and will decide to work with VC investors whose knowledge is different from theirs, not similar as is the case with younger startups.

Older startups have some knowledge reserves accumulated that they can then use to grow (Kogut and Zander, 1992). Much of this results from ”analysis of feedback” (Huber, 1991, p. 91) over many cycles of experimentation. Experiential learning can be defined as the knowledge organizations develop from experience after their birth (Huber, 1991). The knowledge develops as a result of both direct experience and ”availability and analysis of feedback” (Huber, 1991, p. 91). This experiential learning can be a valuable asset, but startups tend to so be limited in their scope (McGrath et al., 1992) that their expertise is bounded to the industry and technological area in which they are active (McGrath et al., 1992). Given the restricted domain of their experiential learning, this allegedly helpful knowledge can lead to competency traps that hinder the development of new knowledge, routines and capabilities (Hashai and Zahra, 2021). These worsen when executives rely too heavily on their past shared knowledge and routines, which we already know is limited given narrow industry and technological focus. Competency traps highlight the potentially dysfunctional effects of ensuring early imprints that can handicap adaptation and stifle growth. To circumvent these harmful effects of redundant knowledge and also to reinforce areas in which knowledge is lacking to begin with, startups choose to work with VC investors with knowledge that complements their own.

The venture capital literature has considered deal syndication as one way to circumvent problems of too much knowledge similarity. Firms intentionally assemble deal teams with a diverse array of skills. Another way, which might be more efficacious for early-stage deals that are too small for syndication, is by matching internal deal teams based on complementary knowledge. In addition, the positive effect of knowledge similarity has been understood, but not necessarily the outcomes associated with knowledge dissimilarity (Makri et al., 2010). Those studying M&A or IPO outcomes tend to focus on scientific knowledge and patent activity but don't measure general financial knowledge, which we know is one of the key ways in which VCs add value (Hsu, 2004b; Sapienza, 1992).

Brander et al. (2002) find evidence that VCs add managerial value to investments, rather than select the best ones that were performing well prior to investment. They conclude that "management rather than selection is at the heart of venture-capitalist activity" (Brander et al., 2002, p. 426). Management involves not just providing capital, but also guiding investments through uncertain terrain and helping them grow (Gompers and Lerner, 2004). A big part of this is helping them navigate the market and gain insight into key movements. This requires general business knowledge. The startups being funded also need to have granular technical knowledge about how to run their businesses. The combination of these two types of knowledge is what creates value for the business upon ultimate exit (Vergara et al., 2016). Furthermore, these two types of knowledge are not just different, but are also be mutually beneficial.

Startups want to partner with VCs who can contribute new skills that enhance the ones they already possess. Hsu (2004) analyzes financing offers made by VCs to startups and found that offers made by VCs with a strong reputation are more likely to be accepted and also are actually lower than other offers made to the startup (Hsu, 2004b). This indicates that startups are not just motivated by money; they want to work with those with better information too (Hsu, 2004b). Megginson and Weiss (1991) suggest that these findings are not surprising because “one of the services that entrepreneurial firms purchase with VC funding is easier access to capital markets and the ability of venture capitalists to reduce asymmetrical information in the offering process” (Megginson and Weiss, 1991, p. 883). Since other parties can be secretive about disclosing proprietary knowledge (Gompers and Lerner, 1999), the best chance a startup has of learning important market information or advancing its own position is by working with a knowledgeable venture capitalist.

Tian (2012) also finds that startups backed by VC firms have higher IPO valuations upon exit. One of the reasons for this is that different VC investors contribute ”heterogeneous skills” to managing the venture (Tian, 2012, p. 246). The reason heterogeneity is important becomes more obvious when we consider the different types of tasks a startup has to perform before it can IPO. Entrepreneurial firms need to recruit members of its team, which investors evaluate when giving it funding (Gompers et al., 2020), develop its customer relations functionality, and coordinate logistics with customers, suppliers and venues (Gompers and Lerner, 1999). They also need market intelligence and fundraising capabilities, which provide startups with some much-needed stability. It’s not necessary to assemble a syndicate team of multiple co-investors to access the different skills required for these tasks; it’s possible to coordinate team members with diverse skills instead. Entrepreneurs possess creative and technical skills, but need VCs for their business acumen; VCs can offer expertise in marketing and selling a product, while entrepreneurs create the product that needs selling (Casamatta, 2003; Fairchild, 2011). Both are necessary for success. If VCs focus their time on building their information networks and business acumen, which requires knowledge from

MBA degrees, they need to rely on the STEM knowledge held by startup entrepreneurs. The two types of knowledge together create synergies necessary for growth (Vergara et al., 2016)

Startups expand their knowledge bases over time, increasingly relying on their own knowledge in pursuit of growth. Early in a startup's life, the match of specific knowledge to the external environment tends to drive growth, particularly when founders can leverage shared work experience to function effectively as a team. However, later in startups' lives, pre-entry knowledge becomes less important (Hashai and Zahra, 2021).

Hypothesis 2: In the late stage of their development with regards to profitability, startups perform better if they share low knowledge similarity with their VC investor

1.2 Data and Methods

1.2.1 Empirical Setting and Data Description

For my empirical analysis, I leverage data from PitchBook, a private database that curates information on venture capital investments and venture portfolio company outcomes.[1] These data skew towards high-tech sectors such as software, information technology, pharmaceuticals and biotechnology, communications and networking, and medical devices. These data are primarily comprised of venture capital firms operating in the United States, located

[1]I gratefully acknowledge a university research grant that provided the funds for the data after negotiating access from the database providers.

in traditional technological hubs including Silicon Valley, New York City, and the greater Boston area. To focus the analysis on the modern period of venture capital investing, where there is a more established status hierarchy, I include in the sample investments made by venture capital firms from 1990 to 2018. These data are comparable to existing sources such as VentureXpert/ThomsonOne and Preqin in terms of industry, geographic, and temporal distribution. A useful feature of Pitchbook's data for studying coordination dynamics in venture capital is that the data identify within each syndicated investment round which firm serves as the lead investor.

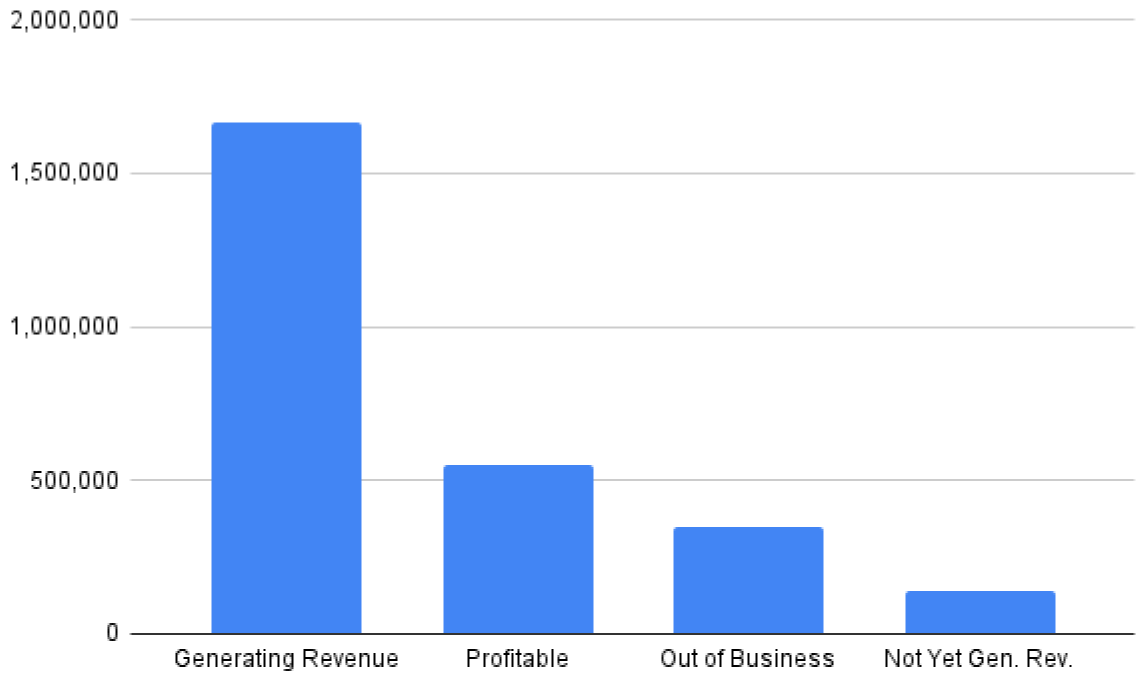
A useful feature of the dataset is that it contains detailed information on the educational backgrounds of each person on the VC investor's deal team and also each person at the startup. I can see which institution granted the degree, when, and in what (degree major and bachelor's or graduate). Based on this, I can code each person as having a business background (1) or not (0), based on if the person has an MBA or undergraduate business degree. I thought the business background is the most relevant dimension, as prior literature has identified that VC investors add value by contributing managerial skills and startups are more than willing to pay for this affiliation, indicating that these skills do contribute to firm outcomes (Hsu, 2004b). I can do the same for a STEM background (graduate or undergraduate degree in science, technology, engineering, or math fields). The presence of individuals who graduated from "Ivy plus" universities is also of theoretical significance in explaining entrepreneurial returns (Lerner and Malmendier, 2013).

1.2.2 Measures: Dependent Variables

Performance

Following literature on venture capital firm performance (Gompers and Lerner, 2004; Hochberg et al., 2007; Sørensen, 2007), the variable *IPOs* measures deal performance. For each deal that exits, I calculate a binary measure: 1 if it exits via IPO, 0 if not. In this way, my goal is to connect a venture's ultimate performance to different attributes of its VC investing deal team and startup team.

Business Status All startups in my dataset have a business status, which reflects if the startup is generating cashflows, regardless of exit type. This is not about a prior financing event, but rather indicates where the company is on its path towards its goal of profitability.



The vast majority of businesses are either profitable or generating revenue. Some have already entered bankruptcy, but that only represents 4.5% of investments being funded. Also interestingly, investments that exit via IPO tend to require fewer rounds of financing than those firms that fail to exit, giving support to the ”move fast and break things” view of new venture development (Taplin, 2017) in which firms are encouraged to proceed quickly and not pause before attempting to pivot, even though a pause might be beneficial (Earle et al., 2019).

1.2.3 Measures: Independent Variables

Similarity Measures

I organized the data so that every member on the VC deal team is matched to every executive team member of the startup it invests in. For example, if there are five members of the VC deal team, individuals $1, 2, 3, 4, 5$ and five members of the startup team, A, B, C, D, E, I examine pairs $A, 1, B, 1, C, 1, D, 1, E, 1$ and so forth.

I was able to determine whether or not there is a match for each pair based on this methodology.

STEM Match looks at if both the VC and entrepreneur both have a STEM degree

MBA Match looks at if both the VC and entrepreneur both have an MBA degree

Knowledge Complementarity equals 1 if the VC and entrepreneur both have different educational backgrounds, which are therefore dissimilar and complementary. For example, if one has an MBA degree and one has a STEM background, the value is 1. If this not the case, the value is 0.

1.3 Results

Table 1 shows a logit model at the deal level, with an outcome variable of 1 if the investment achieves an IPO and 0 if it does not. I run the logit regression (IPO or not) only for all firms that exit. These will be later stage by definition. IPOs are generally assumed to be highly desired outcome for VCs and a well-accepted measure of performance (Gompers, 1996; Krishnan et al., 2011; Lee and Wahal, 2004) The results indicate that match is significant and beneficial for all startups that ultimately exit. Having one more matched dyad on the VC-startup team increases the likelihood of that investment exiting via IPO by e^{β}, or 1.44 and 1.09 times for STEM Match and MBA Match, respectively.

The positive and significant coefficient for *Knowledge Complementarity* indicates that a lack of match drives performance. In other words, having a deal team where a VC investor has an MBA degree and a startup deal team member has a STEM degree, or vice versa, will increase the likelihood of that investment exiting via IPO. What matters is not that these two degree types are merely different; combined, the two together enhance value for the company at exit.

Table 2 shows the estimates for a multinomial logit analysis, relative to the referent group outcome of "Generating Revenue." This analysis is for all firms (both early- and late-stage), regardless of exit outcomes, and I chose the referent group as the most frequently occurring category of business outcomes within my sample of all firms. If a startup were to increase the STEM match or MBA match within its combined deal team with the VC investor, the multinomial log-odds for achieving profitability for the startup relative to only generating revenue would be expected to increase by 0.262 or 0.028 units, respectively, while holding all other variables in the model constant. This corresponds to a likelihood of that investment achieving profitability by e^{β}, or 1.30 and 1.03 times for STEM Match and MBA Match, respectively. The effect of *Knowledge Complementarity* on the log-odds of achieving profitability is also positive, which suggests the combined effect of different types of skills and degree types on the deal team is greater than having either STEM or MBA knowledge alone. The effect of *Knowledge Complementarity* is negative for firms not yet generating revenue, which tend to be early-stage firms that have not yet reached this milestone. An increase in STEM or MBA match also results in a decrease in the log-odds of going out of business.

In other words, having a match is good for profitability. The effect of *Knowledge Complementarity*, or lack of a match, is positive for later stage firms as they reach profitability. The effect on the log-odds of going out of business is negative; said differently, *Knowledge Complementarity* is beneficial for the startup as it progresses towards later stages.

The interaction effects tell more of a nuanced story. As the *VC Deal Round* increases, having an *MBA match*, which occurs when at least one VC-startup dyad pair associated with an investment has their MBA degrees, is not helpful to achieving any of the business outcomes listed. This is not entirely surprising, as I did expect that as a firm progresses into later stages, as the higher round indicates, a match will not positively impact profitability. The effect of a *STEM Match* on the outcome "Not Yet Generating Revenue" is negative, but it becomes very slightly positive for the other business outcomes. *Knowledge Complementarity* indicates the presence of different but mutually beneficial skills. When combined with a higher VC deal round, the effect is negative on the outcome "Not Yet Generating Revenue" but positive for reaching profitability. The interaction is again negative when considering the outcome of going out of business. Taken together, the effect of an MBA match or STEM match on profitability is decreasing as startups receive increasing levels of funding, or as it progresses to a later stage of development. The effect of knowledge complementarity on profitability increases with more funding. These results suggest that at the later stages of a startup's development, similarity in knowledge matching is less important than working with an investor that has different skills and can help the startup grow.

These results are consistent with what was presented in Table 1.

1.4 Conclusions

It is interesting that both similarity and complementarity enhance value for late-stage firms. One possible explanation here is that individuals with complementary knowledge are actually similar in other ways that go beyond degree types, like belonging to the same university. The knowledge is complementary, or dissimilar, on first glance, but the individuals are more similar than it first appears.

It is also possible that two people with different types of degrees are shown to have complementary knowledge, but their areas of expertise are not as unrelated as it may seem. For example, someone who studied mathematical economics (STEM) and another with an MBA with a concentration in financial economics might have more in common than it appears initially.

In the next portion of this thesis, I extend this analysis of knowledge similarity to discuss network structure and implications for firm performance. This area of study still remains limited despite recent research, and it is crucial to understand how firms adapt given their existing knowledge competencies.

Table 1: Logit regression (IPO or not) for all firms that exit

Similarity Variable	**Model 1**
STEM Match	0.368***
	(0.003)
MBA Match	0.090***
	(0.004)
Knowledge Complementarity	0.237***
	(0.004)
Intercept	-1.342***

Table 2. Multiple logit by business outcome for all firms

Variable	Not Yet Generating Revenue	Profitable	Out of Business
STEM Match	0.210***	0.262***	-0.037***
	(0.007)	(0.004)	(0.004)
MBA Match	0.029**	0.028***	-0.122***
	(0.009)	(0.005)	(0.006)
Knowledge Complementarity	-0.194***	0.119***	-0.091***
	(0.010)	(0.005)	(0.006)
Interaction with VC Deal Round			
VC Deal Round*MBA Match	-0.000***	-0.002***	-0.003***
	(0.000)	(0.000)	(0.000)
VC Deal Round*STEM Match	-0.002***	-0.000*	0.000*
	(0.000)	(0.001)	(0.000)
VC Deal Round*Know. Comp.	-0.002***	0.002***	-0.001***
	(0.000)	(0.001)	(0.000)
Intercept	-2.625***	-1.384***	-1.473***

2 The Importance of Structural Positioning

2.1 Theory

We know the importance of deepening our understanding of performance in markets where uncertainty is high and quality is hard to detect. However, if we want to understand firm performance, we need to first understand the firms involved, and our knowledge of the interlinkages between organizational structure and performance still remain limited despite recent research. Findings from network research examine how brokerage across structural holes and closure are both beneficial and how organizations can leverage partnerships to access the benefits of both (Ter Wal et al., 2016a). While brokerage is traditionally thought to yield the most information advantages, most organizations are not—and should not—be composed entirely of brokers. Then the question becomes how can they still benefit from brokerage even if they have a different network structure?

The answer is in forging meaningful partnerships and examining the organizational network structures of those we work with. Network structure is important in explaining how actors acquire and assimilate information. Existing research has tended to explain network evolution as series of independent, discrete events, rather than as the entire sequence of events that takes place over time (Kim et al., 2006). However given the dynamics of any evolutionary process, we'd be better off examining network evolution as one sequential story about an organization's development. Just as all living organisms have different needs at different stages of their lives, so too do organizations—measuring life-stages is harder for organizations than for humans though. The structural holes versus closure debate is crucial in understanding an organization's different needs. It addresses how networks balance access to diverse information and new ideas with shared knowledge that fosters cohesion (Reagans and McEvily, 2003; Burt, 2004; Ter Wal et al., 2016a, 2020). Brokerage and closure are not in conflict so much as they evoke different mechanisms. While one is about increasing variation within a group, the other is about reducing variation and increasing similarity (Burt, 2007). Before an organization can realize the returns from brokerage, it needs to first foster trust from closure (Burt, 2007). The two are complementary, and both are needed to achieve success. This can explain the results we saw in the first part of this thesis.

Brokerage occurs when a network actor occupies a position between two otherwise disconnected actors (Kwon et al., 2020). This gap is referred to as a structural hole, and each actor being connected is holding mainly unrelated information (Burt, 2004). The presence of a structural hole represents an opportunity to coordinate information between two groups and close the gap in knowledge (Burt and Merluzzi, 2016). Actors in brokerage positions, who are able to connect these structural holes, are exposed to a greater variety of non-overlapping knowledge flows and non-redundant information held by disconnected members in their network Granovetter (1973); Burt (2004). As a result, brokers are able to have more novel ideas (Burt, 2004), recognize entrepreneurial opportunities, creatively integrate diverse information, and generate a stronger vision of future possibilities (Burt et al., 2005). Organizations, especially those in creative industries, need brokers who can synthesize ideas that would otherwise be left unconnected.

Organizations also need those with deep, specialized knowledge, who can initially generate ideas before they are bridged. This type of knowledge largely results from network closure, which occurs when network elements are strongly interconnected (Burt, 2017). Those people with specialized knowledge also need to solve complex problems, which involves iterative discussion, is time-consuming, and requires close relationships characterized by trust. The act of solving complex problems can be costly to a firm unless it has people to connect the dots—which is what the brokers in an organization do (Burt, 2017). Garicano finds that knowledge is organized such that "knowledge of solutions to the most common or easiest problems is located in the production floor, whereas knowledge about more exceptional or harder problems is located in higher layers of the hierarchy" (Garicano, 2000, p. 875). In other words, uncomplicated knowledge tends to be concentrated at the lower levels of the hierarchy, while complex knowledge is required higher up. Knowledge is located in different areas of the firm, and there needs to be enough individuals to synthesize that knowledge. Organizations with more complex knowledge need specialists to first generate the foundational ideas, and then brokers can connect those findings.

The argument that network closure and brokerage across structural holes are not actually mutually exclusive, despite commonly being treated as such, is not new—but it is underexplored (Burt, 2000, 2017). "Brokerage across structural holes is the source of value add, but closure can be critical to realizing the value in structural holes" (Burt, 2017, p. 31). Both brokerage and closure create social capital, which is the advantage one receives as a result of its social position (Bourdieu and Wacquant, 1992). This argument is about network span, but others, notably Coleman, argue that social capital is also the result of trust, norms, and routines. Information is more easily accessed in a dense network with more closure, but that information is also more redundant and less novel (Coleman, 1988). So which is "better"—brokerage or closure? The tension between the two can be resolved if we consider a generalized model of networks (Burt, 2017). For example, let's consider the example of the Maghribi traders in North Africa (Greif, 1993). These traders worked closely with one another, but each individually sold goods to those in cities far away (Greif, 1993). Trust was high among the traders, but they also relied on high brokerage externally in order to profitably sell their goods (Greif, 1993). Network closure is critical in the success of the traders, but so too is brokerage (Greif, 1993). Closure and brokerage can also exist together in other types of organizations that can be broken into organizational sub-units. People in those units sometimes need to work together and benefit from closure, but at other times, having a wide network span across other units across the firm is needed.

Furthering the argument that the two together is most beneficial, Burt and Merluzzi finds that organizations with networks that swing between a "period of deep engagement in a group (closure), followed by a period of connecting across groups (brokerage)" (Burt and Merluzzi, 2016, p. 368) enjoy better results, in this case from higher compensation, than those with stagnant network types. The advantage such "oscillation" provides stems from the ability to produce knowledge synergies by combining unconnected, divergent ideas with the trust fostered within dense clusters (Burt and Merluzzi, 2016). Without the cohesion and high closure, the connections made across holes wouldn't stick to produce an advantage (Burt and Merluzzi, 2016); the positive effect of knowledge diversity is activated by high initial density and closure. It is important to note that timing is only essential for an advantage if we focus on timing across one organization. In my context, I look at the partnership with a VC investor and a startup investment. As we can consider multiple network types at once, looking over time is not necessary. We know that startups are small and close-knit teams characterized by high closure (Gompers et al., 2016; Ter Wal et al., 2016a). Therefore, they can realize the benefits of brokerage by working with VC investors that are larger and have information advantages in this area. VC investor firms can also have high closure, at the same time, since they are typically organized by investment strategy or industry sector (Lerner, 1994).

We know that startups care about the network diversity of their VC partners that create value through their brokerage capabilities (Hsu, 2004b; Burt and Merluzzi, 2016). This is especially true of VC firms that create returns for their investments by gathering divergent market information and actively managing startups (Hsu, 2004b). Not all groups need to experience network oscillation to reap the associated advantages. For them, the optimal scenario is one in which an organization with a cohesive network partners with another group that has a more expansive network with more holes.

Ter Wal et al. also reconcile knowledge complexity with network structure to reach similar conclusions. They ask how network actors can access diverse information that they can also effectively interpret (Ter Wal et al., 2016b, p. 394). The answer is by being embedded in closed, densely connected networks that can allow access to detailed and in-depth information that is also easier to interpret (Ter Wal et al., 2016a). Both brokerage and embeddedness simultaneously are advantageous to a firm. Ter Wal et al. (2016) suggest syndicated investments in venture capital, where several VC firms work together to jointly invest in a single startup, as one way actors in one network type can access the benefits of another. However, I suggest that instead of bringing in new knowledge from new VC investors, startups and a single VC can work together more effectively by considering each other's network structures. Specialized knowledge is need for initial growth in the startup, but working with a VC with lots of holes in its network will allow for and sustained performance.

Knowledge similarity and network similarity both need to be understood, given that a key determinant in a network-based advantage is knowledge diversity. One type of similarity tells us what knowledge exists within different VC-startup teams; the second examines how that knowledge is structured within the VC organization. By looking at both combined, we can understand if there is a joint effect on performance. By looking at what information is already present, how it is structured, and what tasks an organization needs to complete before progressing to another stage, we can think about what combinations of network type and knowledge type will maximize performance.

Hypothesis 3: Startups perform better if they are funded by VCs whose knowledge more closely aligns with their startup investments and whose networks span more structural holes.

2.2 Data and Methods

2.2.1 Empirical Context

I use data from PitchBook, a private database that curates information on venture capital investments and venture portfolio company outcomes. These data skew towards high-tech sectors such as software, information technology, pharmaceuticals and biotechnology, communications and networking, and medical devices. These data are primarily comprised of venture capital firms operating in the United States, located in traditional technological hubs including Silicon Valley, New York City, and the greater Boston area.

A useful feature of the dataset is that it contains detailed information on the educational backgrounds of each person on the VC investor's deal team and also each person at the startup. I can see which institution granted the degree, when, and in what (degree major and bachelor's or graduate). Based on this, I can code each person as having a business background:

$$\begin{cases} 1, & \text{if yes} \\ 0, & \text{otherwise} \end{cases}$$

I thought the business background is the most relevant dimension, as prior literature has identified that VC investors add value by contributing managerial skills. I did the same for a STEM background (graduate or undergraduate degree in science, technology, engineering, or math fields), which is common among startup founders in my dataset. The presence of individuals who graduated from "Ivy plus" universities is also of theoretical significance in explaining entrepreneurial success and financing returns (Lerner and Malmendier, 2013).

2.2.2 Measures: Dependent Variables

Next Round

I looked at whether the early-stage firms in my sample proceeded to the next round of funding and assigned values based on that:

$$\begin{cases} 1, & \text{if yes} \\ 0, & \text{otherwise} \end{cases}$$

2.2.3 Network Variables

I include as key network measures: (1) a firm's *Structural holes*, measured as its betweenness centrality, (2) its *Network range*, measured as the average distance between the experience vectors of its ties to other firms, as a way to isolate range of knowledge in a firm's network, (3) the highest-degree *k-core* to which a firm belongs, as a more localized measure of its group affiliations (Freeman, 1977; Reagans and Zuckerman, 2001; Seidman, 1983; Ter Wal et al., 2016a; Wasserman and Faust, 1994) and local embeddedness.

University Match looks at if both the VC and entrepreneur both have a degree from the same group of universities that are known to be connected, similar to the Ivy Plus schools outlined by Lerner and Malmendier, which includes the Ivy League schools plus CalTech, University of Chicago, Duke, MIT, Stanford, Cambridge, and Oxford (Lerner and Malmendier, 2013, p. 2420).

2.2.4 Modeling Strategy

Controlling for firm size will account for whether a venture capital firm's own scale might influence the resources it has available to support its investments, thus affecting whether they can complete an IPO or otherwise exit profitably. One option is to control for firm size as the cumulative number of investment deals a firm has participated in, but it's also necessary to control for prior performance, which might influence a firm's ability to manage its investments, as well as assets under management, which measures a slightly different construct than the others mentioned (Bernstein et al., 2016). Since investing in different investment stages is also related to how investment firms utilize knowledge and manage risk, I incorporate controls that are also related to these factors (Knill, 2009), like whether a firm is part of a corporate organization or time since last investment.

I also plan to introduce firm fixed effects for variables that are constant across firms in the dataset. Fixed effects models are critical for estimating the effect of variables that do not change over time (Allison, 2009), but more flexible model types will be needed to measure the impact of variables that do vary (Hill et al., 2020).

2.3 Results

Table 1 shows a logit model at the deal level, with an outcome variable of 1 if the investment proceeds to the next round of funding and 0 if it does not. The results indicate that having more structural holes and high network range are both positively associated with funding outcomes for early-stage firms. High k-core, a measure of local network embeddedness, and membership in a common set of universities both are associated with better funding outcomes as well. When I interact *Structural Holes* with *MBA Match* and *STEM Match*, these variables are both positive.

Both sets of results indicate that a high number of structural holes and a high network range, or in other words, wider distance of knowledge spanned in the network, are helpful for performance. At the same time, high K-core and common university membership are also beneficial for funding outcomes. This suggests that both brokerage and embeddedness are needed for strong performance. The main effect of each is positive, but the combined effect is most interesting, given the ultimate goal of helping VCs and startups work better together to foster growth for the firms involved and their communities.

2.4 Conclusions

Contrary to popular belief, most VC investors are not purely driven by profit and instead maintain that their portfolio companies, investors, and the communities they engage with all stand to benefit from aligning profit and impact. Accordingly, my results show that impact will be higher if they take the time to account for matching in knowledge similarity and network types. Profits, IPO activity, and funding outcomes will improve too, which is important for VC investors that need to generate strong returns for fundraising and also for the startups that need to survive for its own employees and its communities. All firms, regardless of if they're giving funding or receiving it, want to work together to maximize the positive effect they have on those around them—whether those entities are other investors, clients, customers, or citizens who live in the community. More research around these issues will help them do that.

Table 1: Logit regression (next round of funding) for all early-stage firms

Variable	Model 1	Model 2
Network Variables		
Structural Holes	0.000***	0.000***
	(0.000)	(0.001)
Network Range	3.718***	3.728***
	(0.002)	(0.002)
K-core	0.004***	0.003***
	(0.000)	(0.007)
University Similarity	0.017***	-0.014**
	(0.005)	(0.000)
Interaction with Knowledge Variables		
Structural Holes*MBA Match		0.009***
		(0.000)
Structural Holes*STEM Match		0.005***
		(0.001)
Intercept	-2.665***	-2.629***

Table 2. Multiple logit by business outcome for all firms

Similarity Variable	Profitable	Out of business
STEM Match	0.262***	-0.037***
	(0.004)	(0.004)
MBA Match	0.028***	-0.122***
	(0.005)	(0.006)
Knowledge Complementarity	0.119***	-0.091***
	(0.005)	(0.006)
Intercept	-1.384***	-1.473***

References

Agarwal, R., Echambadi, R., Franco, A. M., and Sarkar, M. B. (2004). Knowledge transfer through inheritance: Spin-out generation, development, and survival. *Academy of Management journal*, 47(4):501–522.

Allison, P. D. (2009). *Fixed effects regression models*. SAGE publications, Thousand Oaks, CA.

Argote, L., McEvily, B., and Reagans, R. (2003). Managing knowledge in organizations: An integrative framework and review of emerging themes. *Management science*, 49(4):571–582.

Åstebro, T., Bazzazian, N., and Braguinsky, S. (2012). Startups by recent university graduates and their faculty: Implications for university entrepreneurship policy. *Research policy*, 41(4):663–677.

Beckman, C. M. (2006). The influence of founding team company affiliations on firm behavior. *Academy of management Journal*, 49(4):741–758.

Bernstein, S., Giroud, X., and Townsend, R. R. (2016). The impact of venture capital monitoring. *The Journal of Finance*, 71(4):1591–1622.

Bourdieu, P. and Wacquant, L. J. (1992). *An invitation to reflexive sociology*. University of Chicago press.

Brander, J. A., Amit, R., and Antweiler, W. (2002). Venture-capital syndication: Improved venture selection vs. the value-added hypothesis. *Journal of Economics & Management Strategy*, 11(3):423–452.

Burt, R. S. (2000). The network structure of social capital. *Research in organizational behavior*, 22:345–423.

Burt, R. S. (2004). Structural holes and good ideas. *American journal of sociology*, 110(2):349–399.

Burt, R. S. (2007). *Brokerage and closure: An introduction to social capital.* OUP Oxford.

Burt, R. S. (2017). Structural holes versus network closure as social capital. *Social capital*, pages 31–56.

Burt, R. S. et al. (2005). *Brokerage and closure: An introduction to social capital.* Oxford university press.

Burt, R. S. and Merluzzi, J. (2016). Network oscillation. *Academy of Management Discoveries*, 2(4):368–391.

Bygrave, W. D. (1987). Syndicated investments by venture capital firms: A networking perspective. *Journal of Business Venturing*, 2(2):139–154.

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

Chang, S. J. (2004). Venture capital financing, strategic alliances, and the initial public offerings of internet startups. *Journal of Business Venturing*, 19(5):721–741.

Coleman, J. S. (1988). Social capital in the creation of human capital. *American journal of sociology*, 94:S95–S120.

Dimov, D. and Milanov, H. (2010). The interplay of need and opportunity in venture capital investment syndication. *Journal of Business Venturing*, 25(4):331–348.

Earle, A. G., Merenda, M. J., and Davis, J. M. (2019). Strategy-as-process in a technology venture: a case study of pivots, pauses, partners, and progress. *Technology Innovation Management Review*, 9(1).

Eisenhardt, K. M. and Schoonhoven, C. B. (1990). Organizational growth: Linking founding team, strategy, environment, and growth among us semiconductor ventures, 1978-1988. *Administrative science quarterly*, pages 504–529.

Ertug, G., Brennecke, J., Kovács, B., and Zou, T. (2022). What does homophily do? a review of the consequences of homophily. *Academy of Management Annals*, 16(1):38–69.

Fairchild, R. (2011). An entrepreneur's choice of venture capitalist or angel-financing: A behavioral game-theoretic approach. *Journal of Business Venturing*, 26(3):359–374.

Falck, O., Heblich, S., and Luedemann, E. (2012). Identity and entrepreneurship: do school peers shape entrepreneurial intentions? *Small Business Economics*, 39(1):39–59.

Freeman, L. C. (1977). A set of measures of centrality based on betweenness. *Sociometry*, 40(1):35–41.

Garicano, L. (2000). Hierarchies and the organization of knowledge in production. *Journal of political economy*, 108(5):874–904.

Gompers, P. (1996). Grandstanding in the venture capital industry. *Journal of Financial Economics*, 42(1):133–156.

Gompers, P. and Lerner, J. (1999). What drives venture capital fundraising? Technical report, National Bureau of Economic Research.

Gompers, P. and Lerner, J. (2004). *The Venture Capital Cycle*. MIT press.

Gompers, P. A., Gornall, W., Kaplan, S. N., and Strebulaev, I. A. (2020). How do venture capitalists make decisions? *Journal of Financial Economics*, 135(1):169–190.

Gompers, P. A., Mukharlyamov, V., and Xuan, Y. (2016). The cost of friendship. *Journal of Financial Economics*, 119(3):626 – 644.

Gorman, M. and Sahlman, W. A. (1989). What do venture capitalists do? *Journal of business venturing*, 4(4):231–248.

Granovetter, M. S. (1973). The strength of weak ties. *American journal of sociology*, 78(6):1360–1380.

Greif, A. (1993). Contract enforceability and economic institutions in early trade: The maghribi traders' coalition. *The American economic review*, pages 525–548.

Hashai, N. and Zahra, S. (2021). Founder team prior work experience: An asset or a liability for startup growth? *Strategic Entrepreneurship Journal*.

Hennart, J.-F., Kim, D.-J., and Zeng, M. (1998). The impact of joint venture status on the longevity of japanese stakes in us manufacturing affiliates. *Organization Science*, 9(3):382–395.

Hill, T. D., Davis, A. P., Roos, J. M., and French, M. T. (2020). Limitations of fixed-effects models for panel data. *Sociological Perspectives*, 63(3):357–369.

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

Hsu, D. H. (2004a). What do entrepreneurs pay for venture capital affiliation? *The journal of finance*, 59(4):1805–1844.

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

Huber, G. P. (1991). Organizational learning: The contributing processes and the literatures. *Organization science*, 2(1):88–115.

Kim, T.-Y., Oh, H., and Swaminathan, A. (2006). Framing interorganizational network change: A network inertia perspective. *Academy of management review*, 31(3):704–720.

Knill, A. (2009). Should venture capitalists put all their eggs in one basket? diversification versus pure-play strategies in venture capital. *Financial Management*, 38(3):441–486.

Kogut, B. and Zander, U. (1992). Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization science*, 3(3):383–397.

Krishnan, C., Ivanov, V. I., Masulis, R. W., and Singh, A. K. (2011). Venture capital reputation, post-ipo performance, and corporate governance. *Journal of Financial and Quantitative Analysis*, 46(5):1295–1333.

Kwon, S.-W., Rondi, E., Levin, D. Z., De Massis, A., and Brass, D. J. (2020). Network brokerage: An integrative review and future research agenda. *Journal of Management*, 46(6):1092–1120.

Lee, P. M. and Wahal, S. (2004). Grandstanding, certification and the underpricing of venture capital backed ipos. *Journal of Financial Economics*, 73(2):375–407.

Lerner, J. (1994). The syndication of venture capital investments. *Financial management*, pages 16–27.

Lerner, J. and Malmendier, U. (2013). With a little help from my (random) friends: Success and failure in post-business school entrepreneurship. *The Review of Financial Studies*, 26(10):2411–2452.

Makri, M., Hitt, M. A., and Lane, P. J. (2010). Complementary technologies, knowledge relatedness, and invention outcomes in high technology mergers and acquisitions. *Strategic management journal*, 31(6):602–628.

McGrath, R. G., MacMillan, I. C., and Tushman, M. L. (1992). The role of executive team actions in shaping dominant designs: Towards the strategic shaping of technological progress. *Strategic Management Journal*, 13(S2):137–161.

McPherson, M., Smith-Lovin, L., and Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual review of sociology*, 27(1):415–444.

Megginson, W. L. and Weiss, K. A. (1991). Venture capitalist certification in initial public offerings. *The Journal of Finance*, 46(3):879–903.

Nanda, R. and Rhodes-Kropf, M. (2013). Investment cycles and startup innovation. *Journal of Financial Economics*, 110(2):403–418.

Nanda, R. and Sørensen, J. B. (2010). Workplace peers and entrepreneurship. *Management science*, 56(7):1116–1126.

Reagans, R. and McEvily, B. (2003). Network structure and knowledge transfer: The effects of cohesion and range. *Administrative Science Quarterly*, 48(2):240–267.

Reagans, R. and Zuckerman, E. W. (2001). Networks, diversity, and productivity: The social capital of corporate r&d teams. *Organization Science*, 12(4):502–517.

Ruhnka, J. C. and Young, J. E. (1987). A venture capital model of the development process for new ventures. *Journal of Business venturing*, 2(2):167–184.

Sapienza, H. J. (1992). When do venture capitalists add value? *Journal of Business Venturing*, 7(1):9–27.

Seidman, S. B. (1983). Network structure and minimum degree. *Social Networks*, 5(3):269–287.

Simsek, Z., Fox, B. C., and Heavey, C. (2015). "what's past is prologue" a framework, review, and future directions for organizational research on imprinting. *Journal of Management*, 41(1):288–317.

Song, M., Podoynitsyna, K., Van Der Bij, H., and Halman, J. I. (2008). Success factors in new ventures: A meta-analysis. *Journal of product innovation management*, 25(1):7–27.

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

Sorenson, O. and Stuart, T. E. (2001). Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*, 106(6):1546–1588.

Taplin, J. (2017). *Move fast and break things: How Facebook, Google, and Amazon have cornered culture and what it means for all of us*. Pan Macmillan.

Ter Wal, A. L., Alexy, O., Block, J., and Sandner, P. G. (2016a). The best of both worlds: The benefits of open-specialized and closed-diverse syndication networks for new ventures' success. *Administrative Science Quarterly*, 61(3):393–432.

Ter Wal, A. L., Alexy, O., Block, J., and Sandner, P. G. (2016b). The best of both worlds: The benefits of open-specialized and closed-diverse syndication networks for new ventures' success. *Administrative science quarterly*, 61(3):393–432.

Ter Wal, A. L., Criscuolo, P., McEvily, B., and Salter, A. (2020). Dual networking: How collaborators network in their quest for innovation. *Administrative Science Quarterly*, 65(4):887–930.

Tian, X. (2012). The role of venture capital syndication in value creation for entrepreneurial firms. *Review of Finance*, 16(1):245–283.

Uzzi, B. (1996). The sources and consequences of embeddedness for the economic performance of organizations: The network effect. *American sociological review*, pages 674–698.

Vergara, M., Bonilla, C. A., and Sepulveda, J. P. (2016). The complementarity effect:

Effort and sharing in the entrepreneur and venture capital contract. *European Journal of Operational Research*, 254(3):1017–1025.

Wasserman, S. and Faust, K. (1994). *Social Network Analysis: Methods and Applications (Structural Analysis in the Social Sciences, Book 8) 1st Edition*. Cambridge University Press, Cambridge, UK.