How Do Venture Capital Partners Match with Startup Founders?[*]

by

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First draft: January 2009
This draft: March 2010

Abstract

The venture capital market is characterized by personal interactions between VC firms and the startups they finance. Yet we have little systematic evidence of how startup founders get matched with partners at VC firms. By assembling data at the individual partner and founder level, we compare personal similarity-based rationale with resource complementarity-based reasons explaining the likelihood of an investment match. We find that a match is more likely if the two parties share a common ethnicity or have both attended a top ranked university, and particularly so when information problems are more severe. With such similarities, the VC's investment also represents a larger fraction of her total investments. We interpret personal similarity as reducing transactions costs in VC matching rather than proxying quality-based matching. Matching based on VC partner's professional expertise appears to be less determined by their complementarity with the founder's background and more by the current lifecycle stage of the startup. In particular, VC partners with finance or operational capabilities are more likely to match with mature ventures. Our findings shed new light on how personal characteristics and professional expertise can be important in financing situations where informational frictions are severe and investors are actively involved with their borrowers.

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I. Introduction and Literature Review

A central feature of the venture capital market is that matching between borrower and investor is two-sided. On the financial capital supply side, venture capitalists (VCs) select which handful of startups to fund among the several hundred business plans it reviews every year (Fried & Hisrich, 1994; Boocock & Woods, 1997). This selection is difficult because startup quality is widely dispersed and hidden quality problems can be severe in that entrepreneurs may have better information about project quality relative to investors (Gompers & Lerner, 2001; Cochrane, 2006). On the demand side, the entrepreneur must make a decision on which VCs will most reliably provide not only financial capital but also professional services which can spur startup corporate development (Macmillan et al., 1989; Gorman & Sahlman, 1990; Hellmann & Puri, 2000, 2002; Brander et al, 2002).

Despite advances in research on the governance and value-added role of VCs, our understanding of how entrepreneurs get matched with VCs is limited. An anecdotal literature (e.g., Fried & Hisrich, 1994) suggests that social networks and trusted referrals are important in explaining the matching process. A second related literature examines geographic proximity between VCs and startups since pre- and post-investment activity may depend on geographic distance. Before an investment is made, the counterparties have to know about and assess one another, both of which are facilitated by geographic proximity (Stuart & Sorensen, 2001). After an investment is made, co-location can facilitate VCs' ability to both monitor entrepreneurs (Lerner, 1995) and add value to them. A third related literature examines the extent to which successful VCs are the ones which pick (or attract) the most promising venture opportunities in which to invest versus add value to those firms (Brander et al., 2002; Sorensen, 2007; Chemmanur et al., 2009).

We place the VC-entrepreneur matching process at the heart of our analysis by examining VC, entrepreneur, and VC-entrepreneur dyad characteristics in explaining the likelihood of a match in a dataset that includes both factual and counterfactual matches. Unlike the majority of the VC literature, which takes the startup and/or VC firm as the unit(s) of analysis, we provide direct evidence on the personal and professional aspects of VC investments by examining founders and VC partners. Unlike arms-length financings in public companies, the *individuals* who demand venture financing (founders) and the ones who supply it (VC partners) engage in frequent face-to-face interactions during pitching, screening, contract negotiations, monitoring and post-investment interactions.[1] As a preview of our findings, we show that similarity in founder's and partner's ethnicity and education strongly predicts matching, whereas only professional operational experience complementarity (but not other dimensions of professional complementarity) predicts VC-entrepreneur matching. The role of similarity is very important. Having a shared ethnicity almost doubles the likelihood of a match, which has an equivalent effect as a tenfold increase in the distance between VC and company headquarters (e.g., from 20-30 miles to 200-300 miles), which the prior literature suggests as important in VCs' ability to monitor and add value to their portfolio companies (Lerner, 1995).

The individual level of analysis is natural for entrepreneurial founders, as their firms do not have established reputations and rely heavily on human capital. On the VC side, while VC firms have an important reputational element (due to repeated interactions with the market), variation within firm at the VC partner level also matters since individual VC partners take seats in the startup's board of directors (Zarutskie, 2010). Consider the following quote about the VC firm, Kleiner Perkins Caufield & Byers, taken from TheFunded.com, an online community of entrepreneurs who review worldwide funding sources: "Let's face it. The real value of KPCB is it is the 'Tiffany' brand in venture partnering. You take their money because you will (i) hire better sales and financial people and (ii) have an easier time doing follow on rounds if things go reasonably well and you need more money. Unless they are wildly interested in your sector, or you get Brooke [Byers] or John [Doerr] on your board, you are not going to get much assistance from them in growing the business." The quote underscores the heterogeneity of VC value that might be obscured by an analysis strictly at the firm level.

Consequently, we investigate how similarity in personal characteristics and complementarity in professional experience affects the likelihood that a given VC investment is undertaken. To this end, we analyze a novel sample of 1,780 actual matches between founders of U.S. venture-backed startups and partners of VC firms who hold seats at the startup's board of directors, as well as 63,919 counterfactual (but plausible) matches. For each individual person we have access to hand-collected detailed information on ethnicity, university affiliation, education, and work experience (from which we construct measures of personal similarity and professional complementarity). VC

[1] VC partners, of course do not (usually) have sole discretion in approving an investment, but the way in which the partner presents the material, goes about doing due diligence on the potential investment opportunity, etc. can have an impact on the likelihood that an investment materializes.

partners have more business experience whereas founders have stronger backgrounds in science and technology, which is consistent with the argument that each side in the matching process brings important skills to the development of startups.

The role of personal similarity is motivated by arguments from finance pertaining to soft information (Stein, 2002; Petersen & Rajan, 2002; Petersen, 2004; Berger et al., 2005; Cohen et al., 2009) and by arguments from sociology pertaining to homophily, the tendency to associate with common others (Lazarsfeld & Merton, 1954; Rogers & Bhowmik, 1971; Blau & Schwartz, 1984; McPherson et al., 2001). A personal characteristic shared by borrower and investor, for example a common ethnicity, may lower the investor's cost of finding, screening and monitoring the borrower. One way this can happen is through enhanced trust resulting from shared personal characteristics. Fisman (2003), for example, reports that a firm with average characteristics is more than twice as likely to obtain trade credit from a co-ethnic capital provider relative to a non co-ethnic supplier, holding firm quality fixed. A second mechanism resulting in the same outcome involves higher costs to defecting within a social network. Individuals with similar personal characteristics have a tendency to share social networks (Marsden, 1987). As such, deviant behavior tends to be punished faster (since news tends to travel faster within a network) and more severely (to the extent that economic transactions are typically embedded within a network). As a result, we observe economic exchange relying more on relational contracting (rather than more costly formal contracts) when participants share personal characteristics (Greif, 1993; Landa, 1994).

In the context of entrepreneurship, shared personal characteristics can facilitate social networks and economic relationships. In Silicon Valley alone, there are many examples of ethnically based trade associations such as the Chinese American Semiconductor Professionals Association and The Indus Entrepreneur (TiE).[2] Vinod Khosla, a co-founder of Sun Microsystems and subsequently a renowned VC partner, made the following observation about entrepreneurial networks: "people regularly talk to each other, they test their ideas, they suggest other people they know, who are likely to be of the same ethnicity. There is more trust because the language and cultural approach are so similar." (Saxenian, 2006: 77). The importance of personal similarity has

[2] TiE, started from a group of South Asians in 1992, has the mission of "foster[ing] conscious entrepreneurship globally by Educating, Mentoring and Networking." It claims to be the world's largest not-for-profit organization for entrepreneurs, with chapters in 53 cities across 12 countries as of 2009. Furthermore, TiE's members have created businesses with a cumulative market value exceeding $200 billion (www.TiE.org).

more generally been validated in studies of innovation diffusion (Agrawal et al., 2008; Kerr, 2008) and founding team composition (Ruef et al., 2003).

Our analysis shows that personal similarity matters in the VC matching market. We find that a match between a founder and a VC partner is twice as likely when both share the same ethnic background. A match is also more likely if both attended a top ranked university. As further evidence of the importance of similarity, we show that when the founder and VC partner share an ethnic tie or have both attended a top ranked university the VC's investment represents a larger fraction of its aggregate investments in all portfolio companies. These linkages are significant only for early stage investments in industries with higher levels of intangible assets, for which information costs are likely to be more pronounced. These linkages are also more important when the distance between VC and company is greater. These subsample findings suggest that the economic role of similarity is reduce information costs. We infer that lower information costs associated with similar personal characteristics allow VCs to make larger investments.

We next investigate whether complementarity along professional lines influences the matching of VC partners and founders. A range of literature suggests that startups demand professional services that complement their own skills. A VC partner who sits on the board of the startup can, if she has the right capabilities, improve corporate governance (Baker & Gompers, 2003; Hochberg, 2008), help recruit key talent, (Hellmann & Puri, 2002) and assist in external business development (Hsu, 2006). Also, her networks of contacts can provide important new linkages to suppliers and customers (Stuart & Sorensen, 2001), follow-on investors (Bygrave & Timmons, 1992), and investment bankers (Barry et al., 1990).

Because value-adding assistance from VC partners is likely to be factored into pricing in a competitive market, it should be demanded more by founders who do not possess a given capability themselves (Hsu, 2004). Hence, a founder with weak operational expertise should realize larger synergies with a VC partner with strong operational expertise as compared with a founder who himself has strong operational expertise. Consistent with this idea we show that a match is more likely when either the founder or VC partner, but not both, have prior work experience in operations. However, we also find evidence that is not consistent with the complementarity thesis: synergies in either sales work experience or academic research experience reduces match likelihood. For these two professional characteristics, a match is more likely if both founder and VC partner *share* these professional capabilities.

One explanation to our mixed result on matching based on complementarity is that the demand for the VC partner's value-adding tasks may depend less on the founder's human capital and more on the startup's lifecycle stage. If each evolutionary step of startup development requires its own combination of inputs, then the ideal match would be different for a younger company than for an older company. We find supportive evidence of this thesis. VC partners with experience in operations or (non-VC) finance are more likely to match with older and more mature companies, and VC partners with experience in sales are more likely to match with companies that raise smaller amounts of financial capital.

Our final empirical step is to examine a possible alternative explanation for the personal similarity results. Our discussion above suggests that personal similarity acts primarily to reduce transaction costs in the VC matching market through enhanced trust and/or through imposing costs on those defecting within a shared social network. If our measures of personal similarity instead proxy for quality, then the empirical results might be read as suggesting a pairing-off process by which high quality VCs match with high quality entrepreneurs. This process may plausibly explain the finding that VC partners and founders with university degrees from top schools tend to match together. A similar process might hold for ethnically based matching under the view that recent U.S. immigration policies resulted in ethnic immigrants drawn from the right tail of the professional skill distribution. Our empirical strategy is to examine whether startup exit outcomes (going public or being acquired) are more favorable when VC partners share a common top university background or ethnicity with startup founders. In both cases, we do not find such a relationship.[3]

In summary, this paper provides new empirical evidence on how personal characteristics and professional experience matter for how startup founders match with VC partners. In doing so, we lend support to the thesis that personal and relational dimensions are central in VC investments. Our results show that similarity along ethnic and educational dimensions predict the formation of matches of founders and VC partners. Complementarity along professional capabilities has a more ambiguous effect, and the startup's lifecycle stage appear to be a more important determinant for the demand for VC partner capabilities.

[3] We do not evaluate the impact of matching on startup performance more generally for several reasons. First, matches are purposeful and related to expected performance, and so random assignment of matches through natural experiments is not available to identify performance effects. We are also not able to isolate a source of exogenous performance variation, which is required for an instrumental variables strategy. Moreover, it is difficult to address what performance would have been had a counterfactual match been consummated.

The remainder of the paper is organized as follows. Section II introduces our sample and describes the coding of similarity along personal characteristics and complementarity along professional lines. Section III presents the empirical analysis, and Section IV contains a concluding discussion.

II. Data

Sample Construction. The main empirical challenge with studying the VC-entrepreneur matching market is that no database contains comprehensive information on founders' and VC partners' personal characteristics and professional experience. To overcome this limitation we create our own data by first merging information from two separate sources and then hand-collecting the variables relevant for our analysis.

The first data source we use is *VentureEconomics*, which is one of the largest and most complete databases on VC investments.[4] In addition to providing information about VC firms and their financings, *VentureEconomics* lists names of individual board members of venture-backed startups. This information is collected from web pages, news reports, press releases and proprietary surveys. We obtain the name of each partner employed by a U.S. VC firm who sits on the board of a U.S. startup. By focusing our attention on U.S. VC investments, we eliminate any influence of legal or other institutional differences.

It is important to note that we only include partners who hold board seats, thus we do not study partners who are responsible for investments without holding board seats. The board in a venture-backed company is the main arena for interactions between founder and VC partners. Because partners without board seats have few or no interactions with the founder, they do not engage in screening, monitoring and value-adding activities. For these reasons, the economic role of personal similarity and professional complementarity is likely to be considerably more pronounced for partners with board seats than for those without.

Our second data source is *CapitalIQ*, which covers public and private companies around the world. From *CapitalIQ* we extract the name and complete biographies for both partners at VC firms and founders of venture-backed startups. *CapitalIQ* obtains this information from web pages, news

[4] Kaplan et al. (2008) report that the investment coverage of *VentureEconomics* is about 85%. The fact that many companies in *VentureEconomics* report no VC board seats, however, suggests that this part of the data has lower coverage.

reports and press releases. Each biography includes detailed information about the individual's education, school affiliations and professional positions. Even though the biography data are to a large degree self-reported, our results are unlikely to suffer from a self-reporting bias, as the aspects of individual experience we examine are unlikely to warrant concealment.

Merging the company and VC variables from *VentureEconomics* with the biography data from *CapitalIQ* results in our final sample of 1,780 matches between VC partners and founders. Each matched pair represents one involvement between an individual working for a VC firm and an individual who has launched a startup company. Because each startup could receive investments from more than one VC, each founder could be matched with more than one partner. Similarly, because each partner sits on the board of many startups, each partner could be matched with more than one partner. Our sample includes 955 unique startups and 283 unique VC firms. Figure 1 presents a histogram of the year of the VC's first investment in the startup. Most pairs are investments made between the late 1990s to the last sample year, 2007.

Selection Issues. Because our sample, by construction, is limited to matches for which *VentureEconomics* and *CapitalIQ* provide the necessary data, we discuss possible selection issues. The information in both these databases is to a large degree self-reported, and so we are likely oversampling individuals who by virtue of choosing to report information are likely to be affiliated with successful startups or with reputable VCs. Because the information frictions surrounding such high-tier investments are likely to be smaller than for low-tier investments, the economic role of similarity in the formation of matches should thereby be less important for the investments we study. This oversampling would therefore tend to bias our analysis *against* finding any results on the similarity between founder and partner.[5]

We also note that our data only contain information on founders but not other key employees. This focus is driven primarily by data limitations – *CapitalIQ* (and other similar databases) do not provide comprehensive and reliable information that would allow us to identify important individuals who are not founders. It may be the case that some VC partners in our sample have more interaction with a key employee than with a founder. Because we cannot identify such companies and eliminate them from our sample, our results are biased *against* finding a role for

[5] The direction of potential bias, if any, on complementarity of professional experience is less straightforward due to the multi-dimensionality of professional experience by functional area. Individuals can be high quality by having depth in a given professional background, but complementarity for startup business development involves diversity in the functional area in which the founders have weak or no experience.

matching on personal and professional characteristics.

Startup and VC Variables. From *VentureEconomics* we extract variables capturing startup characteristics such as location, industry, and firm age. These variables are not the focus of our analysis but are used as controls in most regressions. Figure 2 shows a histogram of the age distribution of the sample companies. As illustrated in figure 3, the sample has a large fraction of companies from typical venture-backed industries such as “Computer Software and Services,” “Internet Specific” and “Medical/Health.” Figure 4 shows the distribution of the headquarter location of the sample companies. The two largest states are California and Massachusetts.

Table 1 panel A reports summary statistics for startup characteristics. The average company was 2 years old and had a post-money valuation of $37 million at the time of the VC investment. We also calculate various variables related to past success and experience based on the *VentureEconomics* data. For this purpose we extract data on each VC’s full investment history up to the date of each sample investment. During its 16 years of existence, the average VC invested in 155 companies of which 17% went public.

Personal Characteristics. We code a number of variables that capture personal characteristics. Table 1 panel B presents sample frequencies for founders and VC partners respectively. Our first personal characteristic is ethnicity. Based on US patent data, Kerr (2008) reports the 100 most common surnames across the following nine ethnic groups: Groups: Chinese, English, European, Hispanic/Filipino, Indian/Hindi, Japanese, Korean, Russian, and Vietnamese. We complement this coding by carefully examining each biography and identifying individuals of the above ethnicities based on country references (e.g. “was born in Beijing”, “completed his undergraduate at Indian Institute of Technology”). As an illustration of the most frequent ethnicities, 4% of matched pairs have a Chinese partner and 4% have an Indian partner. The corresponding frequencies for founders are 3% Chinese and 1% Indian.

Our second personal characteristic is top university affiliation. We create a variable “University: Ivy Plus” which takes the value 1 if the individual has an undergraduate or graduate degree from Brown, Caltech, University of Chicago, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge and Oxford. We find that about two in three partners have a degree from a top university (21% from Harvard and 15% from Stanford) whereas only 26% of founders hold such a degree.

Our third personal characteristic is gender. We match the first name of each founder and partner with the US Census name file. In cases with no match we look for gender references such as "he", "him" or "his" in the biography. Venture capital is a male world with about 96% of all matched pairs having a male founder/partner. We also collect data on the age of the individual, but do not analyze it because the information is only available for a fraction of our sample (180 out of 1,780 observations).

Professional Experience. We extract information from biographies, which include the professional experience of each founder and VC partner. Table 1 panel B presents sample frequencies. We identify professional experience along two dimensions. We first identify four prior work experience categories: operations, sales, finance, and science/engineering by searching biographies for keywords denoting primary job function in the individual's prior employment experience (the keywords used to identify each experience are reported in the Appendix). An individual could have any combination of prior experience so their frequencies do not sum to 100%. For our sample of matched pairs, 46% of partners have experience in operations, 23% in finance, 29% in sales and 49% in science engineering. The corresponding fractions for founders are 38% in operations, 5% in finance, 16% in sales and 55% in science/engineering. Our second dimension of identifying human capital is based on educational degree attainment. We flag individuals who hold MBA or PhD degrees. While more than half of all VC partners hold a MBA degree, the corresponding fraction for founders is only 14%. More than twice as many founders as partners (25% versus 13%) hold a PhD degree.

Furthermore, while founders have stronger science, engineering and research (PhD degree) backgrounds, venture partners tend to have stronger experience in operations, finance, sales and general business (MBA degree). This is consistent with the argument that because many founders are experts on technology, they may benefit from the business development value-adding assistance of VC partners. To the best of our knowledge, our study is the first to document in a large sample of venture investments the presence of such differences.

Similarity and Complementarity Variables. For each of the three personal characteristics discussed above, we create a similarity variable, which takes the value 1 if *both* partner and founder have the characteristic and 0 otherwise. We also create variables that capture the complementarity of the founder's and the partner's professional experience in a given matched pair. Each complementarity variable takes the value 1 if *either* the founder or partner, but not both, have a certain expertise. Table 2 presents under "Matched Pairs" summary statistics of our similarity and complementarity variables. We discuss these fractions in the next section and compare their magnitude to a sample of counterfactual matches.

III. Empirical Analysis

Construction of Counterfactual Matches. The first part of our analysis is to investigate whether matches between VC partners and startup founders are more likely when there is similarity along personal characteristics and complementarity along professional capabilities. For this investigation we face a choice about how to construct the relevant set of counterfactual matches for each actual match. A counterfactual match is any investment by a VC partner in the founder's startup that would have been possible but unlike the actual match, never materialized. Because we need biography data on the partners of counterfactual matches, the set of counterfactual matches can only be based on investments which are included our sample.

One method of identifying counterfactual matches is to simply put no structure on the sample and generate all possible dyads between the set of VCs and the set of founders. Not only is this difficult computationally for our scope of data, this approach has been critiqued because it does not account for non-independence as each firm enters the dataset many times. An alternative is to randomly sample potential dyads, yet this too has been critiqued because the sparseness of the resulting matrix may miss the realized ties, which contains most of the relevant information. We settle on an alternative sampling method, a modified form of the "case-cohort" sampling approach (as in Stuart & Sorenson, 2001), which has been used for rare-event data across a number of literatures, including epidemiology (disease rates) and political science (military conflicts). We first select all of the factual matches and include them in the sample. We then assemble counterfactual matches by selecting all of the VCs investing in a startup (not resulting in a factual match) in the calendar quarter in which a startup factually received funding. We designate these VCs "at risk" of investing in a focal startup and include them in the counterfactual dataset. We do not impose any restriction that the VC of the counterfactual match must be located geographically proximate to the actual match. We instead account for spatial differences in VC investing by controlling for the distance between startup headquarters and VC headquarters in our regression analysis.

The typical case-cohort method study matches factual to counterfactual matches in ratios ranging from 1:1 to 1:5 then use statistical methods to weight the regression and adjust the standard errors (King & Zeng, 2001). Our approach is to use *all* of the VCs in the market in a given calendar-quarter (yielding 63,919 counterfactual matches), as stated above, rather than randomly selecting from this set of potential matches (which never occur). This process therefore yields a ratio of realized to counterfactual matches of approximately 1:36. In unreported robustness tests, we constrain the counterfactual match ratio to five (selected randomly from the full set of counterfactual matches) per actual match, and obtain similar results.

Results on Match Formation. Table 2 lists the conditional means for similarity and complementarity variables for both the actual match and counterfactual match samples. The difference between these two samples is tested with a Chi-squared test. As for complementarity, we note that an actual match is more likely with "Complementarity: Operations" but less likely with "Complementarity: PhD". We also note that a match is about twice as likely (0.9% versus 0.5%) if the founder and partner belong to the same ethnic group.

While the above univariate differences are illustrative, they do not take into account control variables that might also impact match likelihood. To account for such effects, we run multivariate regressions that include the full set of the relevant matching variables as well as controls. We use rare-events logit regressions, which correctly weight and adjust the standard errors for non-independence. The results are presented in Table 3 where each sequential specification includes additional controls. Standard errors are clustered on founder.[6]

Our main focus is on specification V, which includes the full set of VC and company controls. In line with the univariate comparison, we find that the likelihood of a match is higher when there is complementarity in operational experience but lower if only one of the parties holds a PhD degree. We also find that complementarity in sales experience increases the match likelihood. As the inverse to complementarity is similarity, our results show that founders and partners who both have sales experience or a PhD degree are more likely to match. We interpret these findings as mixed evidence for the thesis that founders match with partners who have different professional experience. We later explore the extent to which VC partner-startup founder matching depends on startup lifecycle stage.

As for the results on personal similarity, the regression analysis confirms the univariate result that a shared ethnicity increases the likelihood of a match. A match is also more likely when the founder and partner have a similar educational institution background, as proxied by

[6] Our results are robust to clustering on VC partner, company or VC firm.

"Similarity: Both From Ivy Plus University." A shared gender appears to decrease the likelihood of a match but this difference is only weakly significant (10% level) in one of the five specifications. Overall, we interpret these findings as supportive evidence of the thesis that founders match with partners who have similar personal characteristics as themselves.

Subsample Results on Match Formation. Our next step is to investigate whether the results differ for subsamples of the data which proxy for differences in information costs. In Table 4 we report the results of regressions based on data subsamples formed according to company maturity (specifications I-IV), distance between VC and company (specifications V-VI) and levels of intangible assets based on industry classification (specifications VII-VIII). The idea behind these subsample splits is that the economic role of similarity and complementarity in match formation is likely to vary with the degree of potential information problems between borrower and investor. Screening and monitoring are likely costlier for less mature companies with more intangible assets. Since data limitations prevent us from estimating each industry's level of intangible assets, we rely on the plausible argument that the industry groups "Communications and Media", "Internet Related" and "Bio Technology" have more intangible assets than more traditional industries. Since data limitations prevent us from estimating each industry's level of intangible assets, we compare VC-backed firms in biotechnology, internet related, and communications/media to VC-backed firms in other industries (shown in figure 3). When compared against firms from these other industries, firms in the first group likely have little or no salvage value, and so VCs investments in these firms are more likely driven by future realization of promising growth opportunities.

Similarly, a greater distance makes it more difficult for the VC partner to physically meet with the founder and attend board meetings, so screening and monitoring costs are likely to be higher for more distant investments.[7] We therefore expect information problems to be more pronounced for an early investment in a less mature company, when the distance between VC and company is greater, and when the company operates in an industry with substantial intangible assets.

The results from the subsample regressions support this expectation—personal characteristics play a more significant role for investments with potentially greater information

[7] Lerner (1995) shows that VCs which are located further from their portfolio companies are less likely to take a board seat. Bengtsson and Ravid (2009) and Xian (2009) show that when the distance is greater, VCs rely on more staged finance and high-powered incentive contracts as a substitute to monitoring.

problems. The coefficients on “Similarity: Both Have Same Ethnicity” and “Similarity: Both From Ivy Plus University” are significant for only early financing rounds (specification I) and less mature companies (specification III). The coefficients have a larger magnitude for companies located at further distance from the VC (specification V), and companies which operate in industries with higher levels of intangible assets (specification VII). Our subsample regressions also include various proxies for complementarity between partner and founder. Similar to our results from the full sample regressions, the empirical pattern on the complementarity variables is mixed.

Results on VC Investment Strategy. Our analysis of match formation reveals that similarity along personal characteristics is important when partners of VCs are paired with founders of startups. Our next step is to investigate whether such similarity not only predicts whether a VC invests in a startup but also the VC’s investment strategy. The prediction is that if information costs decrease with similarity then VCs should make relatively more “aggressive” investments when the partner and founder have more similar personal characteristics.

To test this prediction we relate two different measures of the VC investment strategy to our similarity and complementarity variables. Results of regressions are presented in Table 5. The sample in these regressions includes only the 1,780 actual matches because we cannot create counterfactual investment strategies. Also, the unit of analysis in these tests is the VC firm and not the individual partner because we cannot observe all investments made by each partner.

The first measure, “Fraction VC’s Investment in Company,” is the ratio of the VC’s investment in the company as a fraction of all investment made by the VC in all companies it financed. We calculate this ratio using data from *VentureEconomics*. The numerator of the ratio is the dollar amount that the VC has invested in all of the company’s financing (up to December 2008, which is the cutoff date for our analysis). The denominator is the dollar amount that the VC has invested in all of its portfolio companies. A higher ratio means that the VC has devoted a larger fraction of its capital (from any fund) to the company. As reported in specifications I-III (which are identical except with different sets of control variables), VCs make larger relative investments if the VC partner and founder share a common ethnicity or both have a degree from a top university. We also find that complementarity of finance experience increases the relative size of the VC’s investment.

Our second measure, “VC Invested in Later Round,” captures whether the VC also made a follow-up investment in the same company. This variable takes the value 1 if the VC invested after the financing round for which we observe the realized match between partner and VC firm, and 0 if it did not. Put differently, this variable takes the value 1 if the VC did not stage its investment but provided all its capital to the company in only one financing round. Specifications IV-VI yield a negative relationship between "VC Invested in Later Round" and "Similarity: Both Have Same Ethnicity." A shared ethnicity therefore reduces the likelihood of a staged investment. This relationship is only weakly significant, and not significant in specification VI which includes company state and industry controls. We find a stronger negative relationship for "Complementarity: Operations."

On the whole, our analysis shows that personal similarities, and to a lesser extent professional complementarities, can explain not only whether a VC partner invests in a founder but also what investment strategy it chooses.

Results on Match Based on Lifecycle Stage. Although our analysis of match formations and relative investment size yield strong results on similarity along personal characteristics, we find no consistent pattern on complementarity along professional lines. One explanation for the lack of results on professional complementarity is that a startup's demand for professional experience offered by a VC partner depends primarily on the lifecycle stage of the company. An early stage company with no revenues, for example, may demand a VC partner whose sales experience can help the company attract new customers. In contrast, a late stage company preparing for an IPO or an acquisition may demand a VC partner with a strong finance background.

We investigate the validity of this explanation by regressing dummies capturing VC partner expertise on various proxies for the company's lifecycle stage at the time of the investment. Results of probit regressions are presented in Table 6. The sample in these regressions includes the 1,780 actual matches. In specifications I-III, the dependent variable takes the value 1 if the partner has finance expertise (which she has acquired outside the VC industry) and 0 otherwise. We find that partners with finance backgrounds are more likely to invest in companies that are older, have raised more rounds of financing, and are at a later stage of development. In specifications IV-VI, the dependent variable takes the value 1 if the partner has sales expertise and 0 otherwise. We find that the matching based on partner sales background does not vary with company age or maturity. However, we find that companies which raise lower amounts of financing – presumably because they have existing revenues – are less likely to match with a partner with sales expertise. Finally, in specifications VII-IX, the dependent variable takes the value 1 if the partner has operational experience and 0 otherwise. Similar to the results on finance background, we find that companies that are older and more mature are more likely to receive financing from a partner with operational experience.

In summary, our analysis shows that matching based on VC partner experience can be explained by the company's current lifecycle stage. Whereas finance and operational experience are more important for older and more mature companies, sales expertise is more important for companies that demand additional financing. In conjunction with our earlier mixed evidence of matching based on professional experience, the analysis here suggests matching based on a company's life stage needs rather than on how individual skills complement each other.

Interpreting Matching Based on Personal Similarity. While we have framed and discussed the results surrounding personal similarity as lowering transaction costs (via trust or cost of defection based mechanisms), a possible alternative explanation for the empirical patterns is that our empirical measures of personal similarity may instead proxy for quality, and high quality VCs match with high quality entrepreneurs. If our measures of personal similarity instead proxy for quality, then the empirical results might be read as suggesting a pairing-off process by which high quality VCs match with high quality entrepreneurs. This process may plausibly explain the finding that VC partners and founders with university degrees from top schools tend to match together. A similar process might hold for ethnically based matching in that U.S. immigration policies lead to founders and VC partners drawn disproportionately from the right tail of the professional skill distribution.

Our empirical strategy is to examine whether startup exit outcomes (going public or being acquired) are more favorable when founders and VC partners have similarity along personal characteristics or complementarity along professional experiences. In both cases, we do not find such a relationship, as is documented in Table 7. In the reported analysis we use a "Similarity Index" which is the sum of all previously discussed similarity dummies and a "Complementarity Index" which is the sum of all complementarity dummies. In unreported regressions we include each dummy separately and find, similar to the results on the indices, no significant coefficients. We therefore interpret our results on personal similarity as reducing transactions costs in VC matching rather than proxying a quality-based matching process.

IV. Concluding Discussion

This study aimed to fill a gap in the literature regarding the process by which entrepreneurs get matched with VCs. We investigate the empirical relevance of personal similarity and professional expertise complementarity in the VC market. Our results show that personal similarity along ethnic and top university degree dimensions are both strong predictors of a match. The evidence on professional experience complementarity is, however, more mixed, and matching appear to be primarily determined by the skills of VC partners and the lifecycle stage of startups.

It is useful to situate the results reported here within the context of the literatures on VC and new venture team formation. While we are not able to sharply distinguish the mechanisms driving the matching process between VC investors and entrepreneurs, it is useful to compare the plausible mechanisms in our context with those explicitly or implicitly found in the associated literatures. A first literature examines reasons for VC syndication (e.g., Lerner, 1994; Brander, et al., 2002) and the consequences of varied VC syndicates (Hochberg, et al., 2007). A starting point is the observation that financial constraints are not likely to be the primary driver of VC syndication since the magnitude of VC investments, especially in early stage rounds, are a small fraction of typical VC fund size. Studies examining the impetus for investment syndication broadly analyze selection-based and value creation-based reasons (other theories do exist, but we highlight these theories since they are most germane to our discussion).

In selection-based accounts, VC syndication takes place to facilitate due diligence and assessment processes under the logic that different investors have different opinions and/or expertise with regard to identifying the most promising venture opportunities and entrepreneurs.[8] An information mechanism therefore underlies the selection-based argument in that investor teams are assembled to maximize the chance of selecting the most promising startups in which to invest. Extending team composition from the strictly within-investor realm into the investor-entrepreneur formation realm, we find support for the information transmission mechanism in that ethnic and university ties may be pipes along which information can be shared with the result of dampened

[8] Syndication is most relevant when there is ambiguity in venture quality; if there is no uncertainty about high venture quality, investors would not want to give an investment stake to another investor unless that investor added value to startup business development (which is the subject of the second broad class of theories for syndication). The same logic holds for startup team formation and entrepreneurial opportunities: if a given venture idea is certain to pay off, there would be little incentive for an individual originating a venture idea to recruit or involve other founders without a value-added role.

information asymmetry. The form of the information transmitted could be direct exchange among the parties, norms of trust within a social network, and/or a governance mechanism enabled by shared social networks. In this governance mechanism, defecting behavior will be more costly within a social network because it is likely to be broadcast more quickly and completely within than across social networks. We are unable to distinguish which of these effects may be operating in this context.

In value creation-based rationale for VC syndication, VCs assemble co-investors based on their potential for contributing to new venture business development. Complementary skills, experience, knowledge, networks and the like may facilitate this objective. Extending this rationale to the context of VC-entrepreneur partnering, we find that operational complementarity between VC partners and startup entrepreneurs positively predicts a match, while each of sales and research background are negatively associated with the likelihood of a match. While the former result is consistent with possible value creation via functional background diversity, the latter results appear less consistent. In addition, to the extent that co-ethnicity or common university ties between VC and entrepreneur may improve business development by improving communication flows (e.g., Rogers & Bhowmik, 1971), for example, we also find evidence in support of broader team assembly processes for value creation-based reasons. It is interesting to note that much of the literature on startup founding team formation centers on the value creation potential associated with more diverse teams (which tends to offer more diverse perspectives, and therefore the potential for more novel ideas, but with the drawback of being more conflict-laden or divisive) versus more uniform teams (with the advantage of faster action due to shared backgrounds and worldviews but at the potential cost of "groupthink") (Eisenhardt & Schoonhoven, 1990; Ruef, et al., 2003; Beckman, 2006). This debate can be mapped onto the VC-entrepreneur partnering process, with arguments in favor of more homogeneity (common ethnic and university backgrounds) and those in favor of more diversity (complementarity of functional background). Our results suggest that on average, the net advantages of more uniform VC-entrepreneur teams more consistently outweigh the net benefits associated with more functionally diverse teams. As suggested in the results, we do find important contingencies and overall venture firm lifecycle effects, however.

The information and value-added rationale for team formation are not mutually exclusive, however, as researchers in the VC literature acknowledge (Brander, et al., 2002; Hsu, 2004; Sorenson, 2007; Chemmanur et al., 2009). Our results are consistent with this view, as both our proxies for professional complementarity and especially personal similarity are significant in explaining the likelihood of a VC-entrepreneur match.

While our primary aim is in examining the VC-entrepreneur matching context, an area we believe is both important and understudied, it is possible to speculate about how general the personal similarity and professional expertise complementarity effects are likely to be. We have chosen a context in which there is constrained matching: a given VC partner can only sit on a certain number of boards at a given time, and a given entrepreneurial company can only have a certain number of VC partners on its board. Like other matching contexts in which there is a zero-sum choice involved in that matching with one entity means foregoing other opportunities (e.g., the marriage, job, and college markets), assessing the comparative importance of resources the parties bring to the relationship versus personal similarity factors in explaining matching seems fairly generic.

Our empirical setting of the VC-entrepreneur matching context also involves a different production process distinct from other settings in which social networks play a role, such as common school ties between mutual fund managers and portfolio company managers (e.g., Cohen, et al., 2008). The VC-entrepreneur context has the potential to involve both selection and value-added, and it is the latter process in particular which highlights the role of co-production and makes VC-entrepreneur matching a double-sided selection process. These features distinguish our empirical setting from other investment contexts such as mutual fund portfolio selection.

We end with a few thoughts for future avenues of research given the results reported here. First, it would be interesting to examine the effects of matches made under contrasting processes in the VC market with respect to outcomes such as venture performance. Examining real effects of matches made under different logics would also be interesting. For example, are financial contract terms less onerous for funding when matches are made predominately under personal similarity versus professional complementarity? Does personal similarity matter more when the VC industry expands (which happened in the 1998-2000 and 2004-2008 periods) or when it contracts (which happened in 2001-2003 and 2009)? Finally, how does personal similarity affect entrepreneur-VC interaction during the pre-investment due diligence process and the post-investment board involvement, and with what consequences?

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Appendix: Coding Scheme for Biography Data

Ethnicity

(i) List of Chinese, Hispanic, Indian/Hindi, Japanese, Korean, Russian, and Vietnamese surnames from Kerr (2008)

(ii) References to foreign countries in combination with foreign name

University: Ivy Plus

Brown, Caltech, University of Chicago, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge and Oxford.

Male Gender

(i) List of common first names from U.S. Census.

(ii) References to "he", "him" or "his" in biography

Age

(i) Age mentioned in biography

(ii) Year since graduation from undergraduate institution + 22

Experience: Operations

operational management, Chief Executive Officer, strategic direction and growth, corporate development, strategy, business development, operations, strategic, management, Chief Strategy Officer, operating, Operations, chief operating officer, CEO, COO, development

Experience: Finance

CFO, chief financial officer, finance, financial, financier, corporate treasurer, treasurer, investment banker, Economic, investor, equity analyst, investment, investments, portfolio, portfolios, fund, funds, asset, assets, equity, equities, broker,

Experience: Sales

Marketing, sales, Chief Marketing Officer, salesman,

Experience: Science/Engineering

software research analyst, technology, R&D, principal scientist, technology, technologies, research, engineer, engineering, Research and Development, software engineering, development and delivery, publications, papers, patents, patent, computer science, scientist, CTO, chief technology officer, Architect, designed, design, developed, develop, manufactured, IT, technician, technical, professor of (computer science, etc), Internet security, inventor, clinical experience, Senior Research Investigator, programmer, chief scientist, chief technologist, chief technical officer , technical advisory board, scientific advisory board, physician (cardiologist, oncologist, etc), researcher, senior scientist

Education: MBA

MBA, Master of Business Administration

Education: PhD

PhD, Doctorate, Doctoral

Figure 1 - Year Representation (% N=1,780)

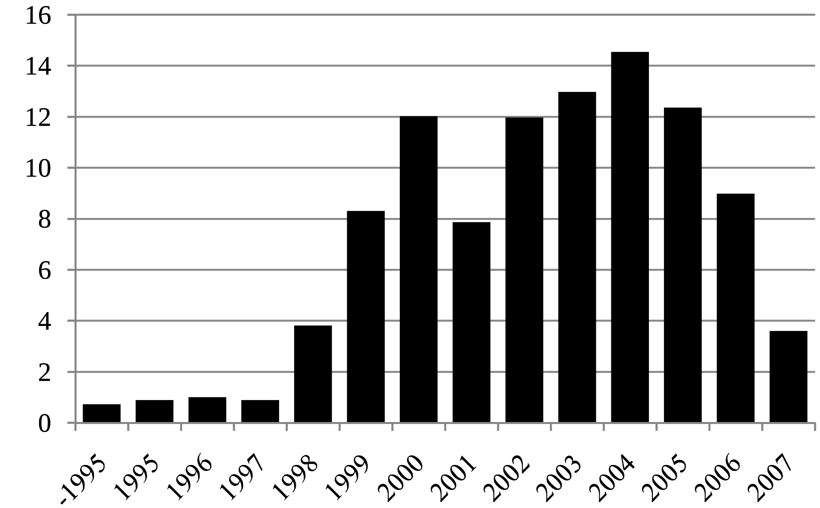

Figure 2 - Company Age Representation (% N=1,780)

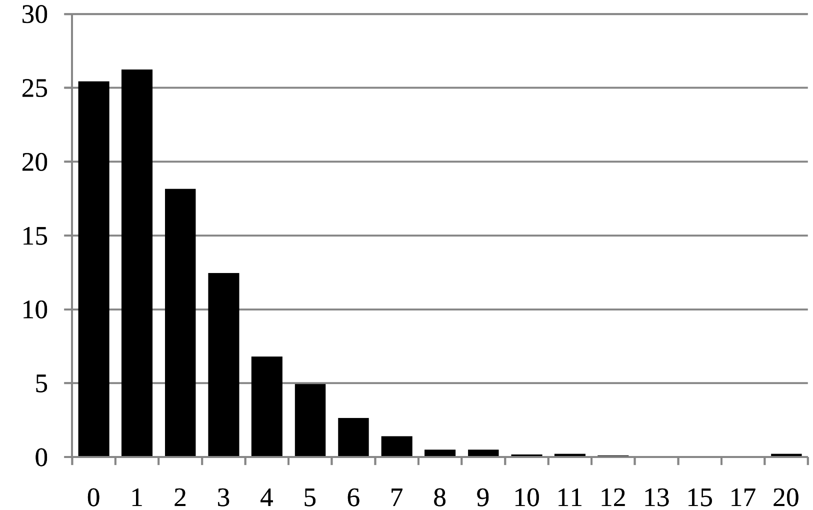

Figure 3 - Industry Representation (%, N=1,780)

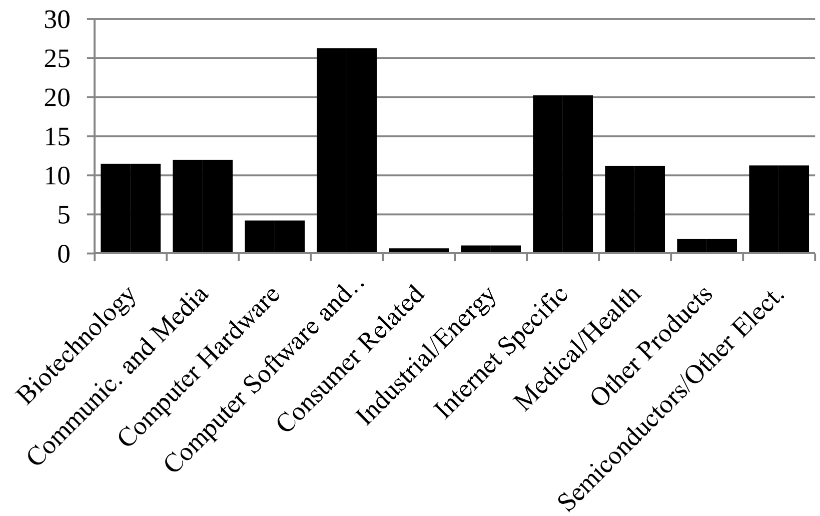

Figure 4 - Company Location Representation (%, N=1,780)

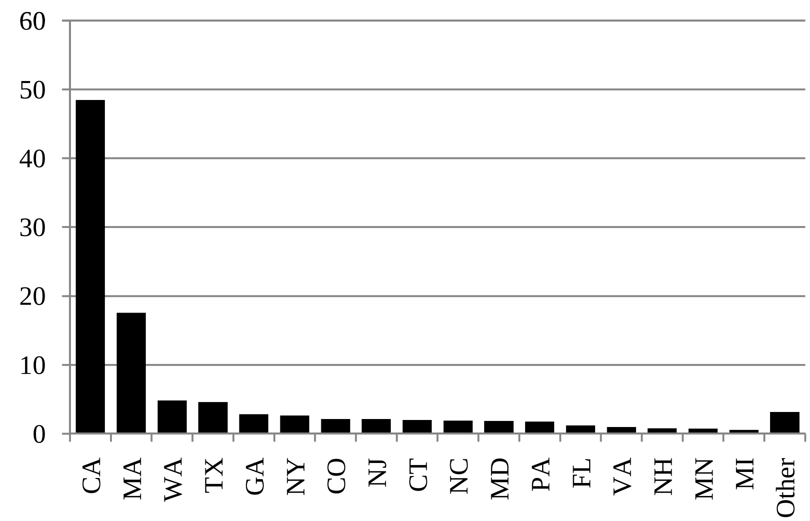

Table 1 - Descriptive Statistics

*Sample is 1,780 matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. The sample is restricted to pairs for which we can identify complete biographies of founder and partner respectively. Biographies are from CapitalIQ. Data on VC firm and startup characteristics are from VentureEconomics. In Panel A, "VC IPO Fraction" is the fraction of all unique company investments with a realized IPO. "VC Number of Portfolio Companies" is the total number of unique company investments. "VC Years Since First Investment" is the number of years since the VC started its operations. In Panel B, "University: Ivy Plus" is Brown, Caltech, University of Chicago, Cornell, Dartmouth, Duke, Harvard, MIT, University of Pennsylvania, Princeton, Yale, Stanford, Cambridge and Oxford. Data on age of partner and founder are only available for 180 observations. Significance from tests of difference of means is marked with *** at 1%. In Panel C, "Fraction of VC's Investments in Company" is the sum of the VC's investment in the company (across all financing rounds) divided by the sum of the VC's investment in all companies (up to December 2008). "VC Invested in Later Rounds" takes the value 1 if the VC invested in a later round of the company, and 0 otherwise.*

Panel A – VC Firm & Startup Variables	Mean	Std. Dev.	Min	Max
Round Sequence	2.10	1.52	1.00	14.00
Early Stage (Dummy)	58%	49%	0%	100%
Company Age (Years)	1.99	2.18	0.00	20.00
Post-Money Valuation ($ thousand)	36,900	57,400	500	967,000
Round Inflow ($ thousand)	12,600	18,000	50	339,000
Distance to VC (miles)	1,359	1,087	0	2,728
VC IPO Fraction	17%	10%	0%	100%
VC Number of Portfolio Companies	154.55	160.07	0.00	779.00
VC Years Since First Investment	15.56	11.36	0.00	47.00

Panel B – Partner and Founder Variables

Personal Characteristics	Partner	Founder	Test Significance
Ethnicity: Chinese	4%	3%	
Ethnicity: Indian/Hindi	4%	1%	***
University: Harvard	21%	5%	***
University: Stanford	15%	7%	***
University: Ivy Plus	67%	26%	***
Male Gender	96%	96%	
Age	51.2	50.9	
Professional Capabilities			
Experience: Operations	46%	38%	***
Experience: Finance	23%	5%	***
Experience: Sales	29%	16%	***
Experience: Science/Engineering	49%	55%	***
Education: MBA	59%	14%	***
Education: PhD	13%	25%	***

Panel C– Fraction on Investment Variables

	Mean	Std. Dev.	Min	Max
Fraction of VC's Investments in Company	2%	4%	0%	66%
VC Invested in Later Round (Dummy)	86%	35%	0%	100%

Table 2 - Conditional Means for Founder-Partner Match

*Sample is matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. "Matched Pairs" reflect the 1,780 actual investments. "Counterfactual Pairs" reflect the 63,919 counter-factual investments made by a different VC partner in a different sample firm in the same quarter. See text for detail. Significance from tests of difference of means marked with ** at 5% .*

	Matched Pairs (N=1,780)	Counterfactual Pairs (N=63,919)	Test Significance
Similarity			
Similarity: Both Have Same Ethnicity	0.9%	0.5%	**
Similarity: Both From Ivy Plus University	44.2%	42.5%	
Similarity: Both Have Male Gender	92.4%	92.9%	
Complementarity			
Complementarity: Operations	51.5%	48.8%	**
Complementarity: Finance	25.6%	26.9%	
Complementarity: Sales	34.8%	36.6%	
Complementarity: Science/Engineering	50.2%	50.2%	
Complementarity: MBA	56.5%	56.0%	
Complementarity: PhD	24.3%	30.2%	**

Table 3 - Founder-Partner Match Rare Event Logits

*Sample is matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. Estimation method is rare event logit. Sample size is 65,699 whereof "Matched Pairs" (dependent variable = 1) reflect the 1,780 actual investments and "Counterfactual Pairs" (dependent variable = 0) reflect the 63,919 counter-factual investments made by a VC partner in a different sample firm in the same quarter. Company/VC characteristic controls are "Round Inflow", "Company Age", "Round Sequence", "Early Stage" and "VC IPO Fraction". Distance controls are "Distance" and "Distance Squared". Company state controls are dummies capturing the location of the company's headquarters. Company industry controls are dummies capturing the 10-segment VentureEconomics industry. See text for detail. Residuals are clustered by founder. Significance marked with * at 10%, ** at 5% and *** at 1%.*

Specification	I	II	III	IV	V
Dependent Variable	Matched Pair = 1, Counterfactual Match = 0				
Similarity: Both Have Same Ethnicity	0.696***	0.701***	0.585**	0.610**	0.629**
	[0.253]	[0.253]	[0.265]	[0.266]	[0.267]
Similarity: Both From Ivy Plus University	0.083*	0.093*	0.087*	0.095**	0.097**
	[0.048]	[0.048]	[0.049]	[0.049]	[0.049]
Similarity: Both Have Male Gender	-0.117	-0.127*	-0.106	-0.119	-0.106
	[0.072]	[0.073]	[0.078]	[0.079]	[0.079]
Complementarity: Operations	0.113**	0.119**	0.121**	0.112**	0.112**
	[0.048]	[0.049]	[0.049]	[0.049]	[0.049]
Complementarity: Finance	-0.097*	-0.091	-0.063	-0.054	-0.055
	[0.057]	[0.057]	[0.057]	[0.057]	[0.057]
Complementarity: Sales	-0.117**	-0.112**	-0.106**	-0.114**	-0.110**
	[0.050]	[0.050]	[0.051]	[0.051]	[0.051]
Complementarity: Science/Engineering	0.01	0.013	0.001	0.002	0.003
	[0.047]	[0.047]	[0.047]	[0.047]	[0.047]
Complementarity: MBA	0.033	0.036	0.02	0.021	0.020
	[0.049]	[0.049]	[0.050]	[0.050]	[0.050]
Complementarity: PhD	-0.314***	-0.320***	-0.357***	-0.334***	-0.392***
	[0.046]	[0.046]	[0.048]	[0.049]	[0.056]
Company/VC Characteristic Controls	No	Yes	Yes	Yes	Yes
Distance Controls	No	No	Yes	Yes	Yes
Company State Controls	No	No	No	Yes	Yes
Company Industry Controls	No	No	No	No	Yes

Table 4 - Founder-Partner Match Rare Event Logits, Subsample Analysis

*Sample is matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. Estimation method is rare event logit. Full sample size is 65,699 whereof "Matched Pairs" (dependent variable = 1) reflect the 1,780 actual investments and "Counterfactual Pairs" (dependent variable = 0) reflect the 63,919 counter-factual investments made by a VC partner in a different sample firm in the same quarter. All specifications include company/VC characteristic controls ("Round Inflow", "Company Age", "Round Sequence", "Early Stage" and "VC IPO Fraction"), distance controls ("Distance" and "Distance Squared") and company industry controls. See text for details. In specification I, subsample is companies in first or second investment round. In specification II, subsample is companies in third or later investment round. In specification III, subsample is companies at seed or early investment stage. In specification IV, subsample is companies at late or expansion investment stage. In specification V, subsample is companies located beyond 1,467 miles from VC headquarters (sample median). In specification V, subsample is companies located beoynd 1,467 miles from VC headquarters. In specification VII, sample is companies in "Biotechnology", "Communications and Media" or "Internet Specific" industry groups. In specification VIII, sample is companies in other industry groups. Residuals are clustered by founder. Significance marked with * at 10%, ** at 5% and *** at 1%.*

Specification	I	II	III	IV	V	VI	VII	VIII
Dependent Variable	Matched Pair = 1, Counterfactual Match = 0							
Similarity: Both Same Ethnicity	0.704**	0.507	0.648*	0.606	1.262***	0.546*	1.072***	0.301
	[0.301]	[0.530]	[0.338]	[0.424]	[0.455]	[0.321]	[0.391]	[0.373]
Similarity: Both Ivy Plus University	0.102*	0.068	0.153**	0.01	0.102	0.085	0.218***	-0.008
	[0.057]	[0.094]	[0.063]	[0.077]	[0.095]	[0.058]	[0.076]	[0.064]
Similarity: Both Have Male Gender	-0.148	-0.015	-0.067	-0.161	-0.363**	-0.022	-0.195	-0.036
	[0.095]	[0.130]	[0.107]	[0.114]	[0.165]	[0.095]	[0.121]	[0.103]
Complementarity: Operations	0.096*	0.197**	0.128**	0.120	0.153	0.105*	0.106	0.133**
	[0.058]	[0.091]	[0.064]	[0.075]	[0.094]	[0.057]	[0.075]	[0.065]
Complementarity: Finance	-0.075	-0.034	-0.087	-0.033	-0.073	-0.103	0.015	-0.128*
	[0.067]	[0.104]	[0.072]	[0.089]	[0.113]	[0.064]	[0.084]	[0.077]
Complementarity: Sales	-0.067	-0.199**	-0.079	-0.134*	-0.058	-0.122**	-0.064	-0.137**
	[0.060]	[0.094]	[0.067]	[0.077]	[0.103]	[0.058]	[0.079]	[0.066]
Complementarity: Science/Engineer.	0.055	-0.068	-0.024	0.085	0.011	0.048	0.028	0.02
	[0.059]	[0.096]	[0.066]	[0.078]	[0.100]	[0.057]	[0.078]	[0.066]
Complementarity: MBA	-0.006	0.024	-0.05	0.072	0.011	0.012	-0.005	0.006
	[0.058]	[0.090]	[0.065]	[0.073]	[0.097]	[0.055]	[0.070]	[0.064]
Complementarity: PhD	-0.363***	-0.534***	-0.369***	-0.492***	-0.451***	-0.351***	-0.472***	-0.278***
	[0.063]	[0.104]	[0.071]	[0.086]	[0.116]	[0.065]	[0.073]	[0.065]
Company/VC Characteristic Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Subsamples Formed On	Round Number		Investment Stage		Distance Comp-VC		Intangible Assets	
Subsample	1st or 2nd	Later	Early	Late	Far	Close	High	Low
Subsample Size	47,682	18,017	38,093	27,606	32,734	32,737	27,146	38,048

Table 5 - VC Investment Strategy

*Sample is 1,780 matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. In specifications I-III, the dependent variable is the fraction of the VC firm's investments made in the sample company. This fraction is calculated by dividing the sum of the VC's investment in the company (across all financing rounds) with the sum of the VC's investment in all companies (up to December 2008). Estimation technique is tobit. In specifications IV-VI, the dependent variable takes the value 1 if the VC also invested in later rounds of the same company, and 0 otherwise. Estimation method is probit with coefficient estimates adjusted to reflect variable means. Company/VC characteristic controls are "Round Inflow", "Company Age", "Round Sequence", "Early Stage" and "VC IPO Fraction". Distance controls are "Distance" and "Distance Squared". Company state controls are dummies capturing the location of the company's headquarters. Company industry controls are dummies capturing the 10-segment VentureEconomics industry. Significance marked with * at 10%, ** at 5% and *** at 1%.*

Specification	I	II	III	IV	V	VI
Dependent Variable	Fraction of VC's Investments in Company			VC Invested in Later Round		
Similarity: Both Have Same Ethnicity	0.039***	0.039***	0.041***	-0.243*	-0.226*	-0.218
	[0.009]	[0.009]	[0.009]	[0.125]	[0.128]	[0.133]
Similarity: Both From Ivy Plus University	0.008***	0.007***	0.006***	-0.012	-0.006	-0.014
	[0.002]	[0.002]	[0.002]	[0.018]	[0.018]	[0.018]
Similarity: Both Have Male Gender	-0.005	-0.005	-0.003	-0.027	-0.027	-0.021
	[0.003]	[0.003]	[0.003]	[0.031]	[0.030]	[0.030]
Complementarity: Operations	0.001	0.001	0.000	-0.037**	-0.035**	-0.037**
	[0.002]	[0.002]	[0.002]	[0.018]	[0.017]	[0.017]
Complementarity: Finance	0.007***	0.007***	0.007***	-0.005	0.006	0.023
	[0.002]	[0.002]	[0.002]	[0.020]	[0.019]	[0.019]
Complementarity: Sales	-0.002	-0.001	-0.001	0.013	0.005	-0.002
	[0.002]	[0.002]	[0.002]	[0.018]	[0.018]	[0.018]
Complementarity: Science/Engineering	-0.001	-0.001	-0.001	0.008	0.009	-0.001
	[0.002]	[0.002]	[0.002]	[0.018]	[0.018]	[0.018]
Complementarity: MBA	0.001	0.000	0.001	-0.004	-0.001	-0.013
	[0.002]	[0.002]	[0.002]	[0.018]	[0.017]	[0.017]
Complementarity: PhD	0.002	0.003	0.001	0.038*	0.034*	0.02
	[0.002]	[0.002]	[0.002]	[0.020]	[0.019]	[0.021]
Company/VC Characteristic Controls	No	Yes	Yes	No	Yes	Yes
Distance Controls	No	Yes	Yes	No	Yes	Yes
Company State Controls	No	No	Yes	No	No	Yes
Company Industry Controls	No	No	Yes	No	No	Yes

Table 6 - Match Probits, Experience of Partner at VC Firm and Company Maturity

*Sample is 1,780 matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. Estimation method is probit with coefficient estimates adjusted to reflect variable means. Dependent variable takes the value 1 if partner at VC firm has a certain background (finance in specifications I and II; sales in specifications III and IV; operations in specifications V and VI; science/engineering in specifications VII and VIII). Company state controls are dummies capturing the location of the company's headquarters. Company industry controls are dummies capturing the 10-segment VentureEconomics industry. Significance marked with * at 10%, ** at 5% and *** at 1%.*

Specification	I	II	III	IV	V	VI	VII	VIII
Dependent Variable	Partner Experience Finance=1 (not=0)		Partner Experience Sales = 1 (not=0)		Partner Experience Operations = 1 (not=0)		Partner Experience Sci./Eng. = 1 (not=0)	
Company Age (Years)	0.011**		-0.004		0.011*		0.008	
	[0.005]		[0.006]		[0.006]		[0.006]	
Early Stage		-0.050**		-0.009		-0.050*		-0.001
		[0.022]		[0.024]		[0.026]		[0.025]
Round Inflow ($ million)	0.000	0.000	-0.003***	-0.003***	0.000	0.000	0.000	0.000
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Company State Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Company Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.041	0.041	0.065	0.065	0.020	0.020	0.017	0.017

Table 7 - Outcome Probits

*Sample is matched pairs of founders of U.S. startup companies and partners of U.S. venture capital firms. Estimation method is probit with coefficient estimates adjusted to reflect variable means. Sample size is 1,077 of actual investments made prior to 2004. Investments during or after 2004 are excluded since venture-backed companies typically need five years to realize an exit. "Complementarity Index" is the sum of all complementarity variables presented in Table 2. "Similarity Index" is the sum of all similarity variables presented in Table 2. All specifications include year and industry controls, and variables that reflect the founder's and partner's experience. Significance marked with * at 10%, ** at 5% and *** at 1%.*

Specification	I	II	III	IV	V	VI
Dependent Variable	IPO = 1, Other = 0			IPO/Merger = 1, Other = 0		
Similarity Index	0.009	0.008	0.007	-0.007	-0.01	-0.011
	[0.008]	[0.008]	[0.008]	[0.017]	[0.017]	[0.017]
Complementarity Index	0.002	0.004	0.007	-0.014	-0.019	-0.017
	[0.017]	[0.016]	[0.016]	[0.033]	[0.033]	[0.033]
Company Age (Years)		0.012***	0.010**		0.041***	0.042***
		[0.005]	[0.005]		[0.012]	[0.013]
Round Inflow ($ million)		0.000***	0.000***		0.000***	0.000***
		[0.000]	[0.000]		[0.000]	[0.000]
VC IPO Fraction			0.242***			0.423**
			[0.084]			[0.192]
Company Industry Controls	Yes	Yes	Yes	Yes	Yes	Yes
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared	0.180	0.230	0.240	0.100	0.120	0.120