

Resource Accumulation Through Economic Ties: Evidence from Venture Capital*

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Abstract

Ties between similar partners in economic and financial networks are often attributed to concerns about agency costs. In this paper, we distinguish the underlying motives for tie formation between sets of potential partners in the network, thus informing the relative importance of agency cost and resource accumulation in tie formation across firms. We develop a robust and generalizable methodology that allows for the inference of similarity and/or cumulative advantage motives in the potential presence of resource trading. We estimate the model using venture capital (VC) co-investment networks, employing factor analysis to characterize orthogonal, interpretable resources for VC firms. In the VC setting, value-added resources other than capital appear to be exchanged for capital, but not for one another. We find little evidence for similarity motives as the primary driver of matching, suggesting that concerns over agency conflicts in partnering are dominated by the desire to accumulate higher levels of certain resources.

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1 Introduction

Economic and financial networks frequently exhibit ties (e.g., syndication activity, strategic alliances, joint ventures, or contracting) between similar partners. Observers often infer that a preference for similarity drives the pairing, particularly as a means to avoid agency costs. However, similarity along a particular dimension can result also from a desire for resource accumulation with highly endowed partners or resource exchange across dimensions with differently endowed partners. In this paper, we propose a rigorous methodology to infer the motives underlying the choice of partner in the formation of such economic ties, and thus inform the relative importance of agency costs and resource accumulation in the formation of economic ties.

We develop a robust and generalizable methodology that allows for the identification of seeking a similar versus highly or differently endowed partner, and estimate our model in a setting in which organizational networks are of primary importance: the VC industry. Our findings suggest that concerns over agency conflicts are not a primary concern in our setting, but instead are dominated by the desire to accumulate distinct resources for the production function. Furthermore, in the VC setting, value-added resources other than capital appear to be able to exist separately from capital and still be exploited effectively.

Organizations form economic ties through shared activity in many financial and product markets. For example, lenders often prefer to syndicate corporate loans over being the sole source of capital; financial institutions tend to co-underwrite securities offerings; biotechnology and pharmaceutical companies regularly engage in strategic alliances and joint ventures for the development of new drugs; and venture capital and private equity firms often syndicate their investments in private companies. These ties form networks that have been shown to influence governance, investment performance, and competition (Robinson and Stuart, 2007; Hochberg et al., 2007, 2010; Lindsey, 2008).

Importantly, while there has been a great deal of empirical work on the *effects* of tie formation, there is little empirical work characterizing *how* and *why* organizations choose the partners with whom they engage in economic activity. In contrast to the literature on social networks among individuals, it is unclear in an organizational setting that explicit preferences for similarity would underlie the motive to tie. Similarity-based motives for organizational network ties are generally

attributed to the avoidance of agency conflicts, as disparate levels of a given resource may lead to expropriation, to hold-up due to informational advantages, or to extraction of rents from different outside options (e.g., Casamatta and Haritchabalet, 2007; Cestone et al., 2007).

Alternatively, firms may choose partners in an effort to aggregate particular resource endowments. They may therefore seek the highest-endowed partner, with the desirability ranking of a prospective partner independent of an organization's own resource levels. We refer to this driver as *cumulative advantage*. Cumulative advantage suggests that output of the production function underlying the shared economic activity is increasing over the observed levels of input, and thus that the input is important to the organization.

Furthermore, organizations may be endowed with multiple resources and, thus, examining similarity versus cumulative advantage alone may not give a complete picture of underlying motives for ties. Given the existence of multiple resources, it is possible that firms also distribute resources, i.e., trade, in addition to aggregating them. If organizations lack the full set of resources required to fulfill their objectives, they may form economic ties to trade distinct resources (e.g., Eisenhardt and Schoonhoven, 1996). Critically, for resource trading to be possible, it must be the case that agency concerns are either sufficiently small or resolvable through other means such that firms with differing endowments can engage in joint activity (e.g., one firm has more expertise and less available capital for investment, while the other firm has more available capital and less expertise). Both cumulative advantage and resource trading reflect a desire to accumulate particular resources for production, and we regard both as different forms of resource accumulation.

To distinguish the underlying motives for network ties, we develop a methodology that allows us to test for the presence of similarity-based matching, cumulative advantage, and resource sharing in the formation of network ties. Existing work in the area tends to examine a single firm attribute (such as experience or location) in isolation, and typically focuses on the question of whether potential partners are similar in that particular attribute, often making inferences from coefficient loadings on differences in the observed level of the attribute for each partner. However, because multiple theoretical motivations for the formation of a partnership may lead to the observation of ties amongst partners that are similar in an attribute, previously employed approaches are insufficient to capture questions relating to the economics underlying organizational ties.

Contrary to what one might expect, we show that it is insufficient to simply interpret negative

coefficients on measures of absolute differences in resource levels between partners alone as evidence for similarity-based motives. Similarly, it is insufficient to interpret positive coefficients on sums of resource levels alone as evidence for cumulative advantage motives. Instead, our methodology explicitly separates the effects of variation in the endowments of the more-highly endowed and the less-endowed partners, allowing us to analyze the two variations separately. We can thus distinguish between gains from partnership that increase when the more-highly endowed partner in a pair becomes weaker or the less-endowed partner becomes stronger (consistent with a desire for similarity) versus gains that accrue when either of the partners in the pair is more-highly endowed (consistent with a desire for cumulative advantage).¹

Our methodology models the gains from tie formation between a pair of firms or organizations as a function of the resources of the pair, as well as interactions among resources, which allows us to capture patterns related to the above motives of tie formation. Under the identifying assumption that ties are more likely formed when the (net) gains from tying are higher, we employ standard latent variable models to estimate the gains model and, thus, interpret the model coefficients as describing the net anticipated gains from the formation of particular types of matches.

The VC setting is a natural laboratory for our analysis. VC firms tend to form ties with other VCs rather than investing alone (Lerner, 1994). At the same time, VCs vary greatly in their investment styles, types, and histories and, therefore, in the resources available to employ in the selection and development of their portfolio companies. In addition, the venture capital industry itself, through the funding and nurturing of startup firms, is an important engine of growth for the overall economy. In 2010, for example, revenue from formerly venture-backed firms comprised 21% of GDP, and these firms employed 11% of the private sector workforce (as reported in the National Venture Capital Association Yearbook, 2012). Since inter-organizational network ties amongst VCs have been shown to affect performance of their portfolio companies, understanding the underlying motives for these network ties is interesting and important in its own right.

¹Importantly, our empirical examination of cumulative advantage and similarity in matching differs from standard assortative matching with the equilibrium constraint of a single tie (e.g., Becker, 1973; Shimer and Smith, 2000), in which the equilibrium outcome is observed similarity, i.e., high types pair with high types and low with low. Both anecdotal evidence and our examination of the data suggest that VCs do not face a similar constraint; rather, they can have multiple simultaneous co-investment partners in multiple portfolio companies and, thus, we are able to observe many more ties between high-type and low-type firms than assortative matching under a single-tie capacity constraint would predict. Importantly, if capacity for tying were sufficiently constrained, cumulative advantage motives would be indistinguishable empirically from similarity-based motives, creating a bias toward finding evidence in support of the search for similar types, which we do not find.

A key feature of our analysis is how we define resources and characteristics for firms. A standard problem in the literature is that many firm characteristics observable to researchers are highly correlated and can be thought of as a proxy for some facet of unobservable or harder-to-quantify resources such as ‘quality.’ Thus, while resources may be observed by market participants and in theory may be orthogonal, the proxies used to represent resources are often inexact and correlated. When resource trading exists and proxies for resources are positively correlated, estimating equations that do not account for resource trading will produce biased coefficients with a tendency to confirm similarity (Hochberg et al., 2015). While our methodology accounts for the possibility of resource trading, our characterization of resources provides advantages in avoiding such issues: we employ factor analysis to identify orthogonal sources of variation in firm characteristics, which we then utilize as measures of resource endowments.

In our particular laboratory of the VC industry, the underlying factors we uncover all have natural, intuitive interpretations. The characterization is parsimonious: we are able to capture 95% of the observable variation across 27 VC attributes with four linear and uncorrelated factors. Because they are constructed to be orthogonal, we can interpret them more easily as separate dimensions of variation. The first factor loads strongly on variables related to VC firm time-in-existence, both generally and as an investor in specific industry sectors, and thus appears to measure *experience*. The second loads strongly on various measures of network centrality, closeness and betweenness, as well as the number of companies in which a firm has recently invested, and thus appears to measure *access*. The third loads strongly on measures of firm assets under management, dollar volume of investment, and uninvested capital and can be interpreted as measuring *available capital*. The fourth loads strongly on measures of VC firm diversity of investment across industry sectors, geography, and stage of investment, and thus measures *investment scope*.

We find little evidence for similarity as the primary driver of tie formation in any of the four resources.² This result is contrary to the predictions of many agency and adverse selection models, which suggest that matching should be sought based on similarity when the resource in question would allow the better-endowed partner to hold-up the less-endowed partner. Only in tying over

²The fact that we do not find support for similarity-based matching at the organizational level does not preclude its existence at the level of the individual human capital present at these firms. For example, Bhagwat (2011) provides evidence that VC firms are more likely to syndicate individual deals with other VC firms that have partners that went to the same school, and Gompers et al. (2012) show additional affinity-based characteristics such as sharing the same ethnic background or having worked for the same employer appear to affect VC syndication.

available capital do we see evidence in support of similarity as a motive for partner selection, but it exists in tension with cumulative advantage motives: as the available capital endowment of the lower-endowed of the pair increases, net gains from tying increase; but an increase in the capital of the higher-endowed of the pair exhibits no relationship to tie formation.

Further, we find that VC firms appear to link based on cumulative advantage with respect to access and investment scope. In other words, VC firms seek partners with better network positioning and with a more generalist approach, and this preference is independent of their own positioning and approach. In contrast, economic ties appear to be enhanced by *dissimilarity* in experience (which we will call ‘anti-similarity motives’ or ‘anti-similarity-based matching’). This finding suggests that not all resources related to the value-added capacity of the VC firm behave in a similar fashion. Importantly, we note that our results are consistent with the observation of similarly aged or sized VCs in the same deals. Because our factors are orthogonal, we are able to separate out the component of age that relates to experience or skill from the component that relates to capital availability or access (Lerner, 1994).³

Looking across resources, we find clear evidence of trading motives. The specific patterns of resource trading are informative and of particular interest: only some resource pairs can be traded while others must be inside the same firm to be used effectively. Anticipated net gains from trade increase when one partner has more available capital and the other is more experienced, has greater access, or greater investment scope, but there is no evidence of gains from trading *across* value-added resources (scope, access, or experience). Thus, our model estimates suggest that net gains from trade are larger when a single firm in the pair is endowed with higher levels of all of experience, access, and investment scope and the other VC in the pair has a high endowment of available capital. Combined with our other empirical findings, it appears that capital can exist outside the firm and be combined effectively with inside value-added but the same does not apply to combinations of inside and outside value-added resources.

³It is also important to note that our methodology considers *resource-based* partnership formation. Two VC firms with the same industry or geographic focus are more likely to form partnerships with one another than are VCs that invest in separate industries or locations as a matter of variable construction, i.e., the categorization of VC firms into industry and geographic focus is based on observed investments, and if two VC firms coinvest in companies more often they will likely develop the same industry or geographic focus. The categorization issue would still apply if the focus were the location of a particular VC firm, rather than company investments, since VCs tend to invest in nearby firms, leading VC firms located near one another to coinvest more often. We use this type of information as a control, confirming results in previous literature, but do not consider it evidence for similarity as a resource-based motive for the formation of organizational ties.

We also examine patterns for VC firms that share indirect ties (two VC firms that share a tie with a third VC firm but not with each other, which we call ‘friend-of-friends’) and VC firms with repeated ties. We find substantially similar patterns for firms with and without indirect ties, and for firms with repeat and new ties. While our specific results are confined to the VC setting, the resource factors we characterize are quite general and might reliably apply to syndicates formed by other financial intermediaries or even to the formation of alliances among firms more broadly.

Our contribution is threefold. First, we make a methodological contribution. To the best of our knowledge, this paper is the first to formalize an empirical model for testing commonly accepted theories of economic tie formation between organizations. Much of the prior literature on motives for inter-organizational relationships relies on indirect measures, such as stock price reactions to the announcement of an alliance (Park et al., 2004) or the presence of dissimilar partners, to infer that resource trading occurred (Chung et al., 2000). Further, a large literature extending the social network concept of homophily to organizational networks tends to test for partner similarity along a single dimension. Testing across competing theories of network tie formation simultaneously can be crucial, particularly if observable characteristics are correlated. Our methodology allows us to provide evidence that resources are traded across co-investment ties in the VC setting, while at the same time allowing for matching motivated by similarity, anti-similarity, and cumulative advantage. We are therefore able to determine which resources are traded and which are accumulated, as well as distinguish between similarity as a motive versus an outcome of an assortative process or an artifact of correlated levels of resources within an organization.

Second, we contribute to the large literature exploring the nature and drivers of alliances and other economic ties amongst firms (see, e.g., Das and Teng, 2000; or Parmigiani and Rivera-Santos, 2011, for an extensive review). Here, we focus on resources of VC partnerships and how these partnerships source additional resources through shared economic activity. In particular, we show that VCs are much more able to externally source capital than they are other resources and that agency concerns are not the primary driver of partner selection. Viewed through the lens of transaction costs (Coase, 1937; Williamson, 1981), our findings suggest that the costs for sourcing certain resources outside the partnership are low relative to the costs associated with coordination of human capital within the VC partnership.

Last, we also contribute to the literature on VC syndication. In contrast to prior empirical

work which focuses on syndication at the level of the individual deal (Lerner, 1994; Du, 2008), we focus on the networks formed from the aggregation of syndicate deals. This approach allows for the influence of externalities that may accrue to the firm beyond the level of an individual deal. Theory has long recognized the need for assembling complementary resources in entrepreneurial ventures (see, e.g., Hellmann, 2007), and a number of studies have explored the value-added activities of the venture capitalist as a financier of entrepreneurial ventures (Lerner, 1995; Hellmann and Puri, 2000, 2002; Hsu, 2004; Hochberg, 2012; Lindsey, 2008). Yet, there has been little empirical work that has explored what these resources are and how they combine to produce these value-added activities. Here, we find that different value-added resources cannot be easily combined when endowed to separate VCs, and that not all value-added resources (e.g., experience) behave in the same way.

The remainder of this paper is organized as follows. Section 2 discusses the empirical methodology. Section 3 describes the sample used in our empirical analysis, including the construction of the resource factors. Section 4 presents the results. Section 5 concludes.

2 Methodology

We consider the network of organizations that is formed through shared economic activity, such as syndication, strategic alliances, or joint ventures. The standard description of a network is a graph with firms or agents as nodes and connections between nodes indicating ties. Each firm node is indexed by $i \in \{1, \dots, n\}$ and has a vector of attributes, X_i which we denote as *resources*. Each pair of firms (i, j) on the graph may also have a set of joint attributes, $\hat{X}_{ij}$, which denote pair-specific attributes. In our setting, these joint attributes consist of resource interaction effects, the existence of a past connection, and having had a common geographic area or industry sector in past investment. The matrix of connections M is $n \times n$, with $M_{ij} = 1$ if firms i and $j \neq i$ form a tie based on shared economic activity in a given time period, and $M_{ij} = 0$ otherwise.

2.1 Latent variable approach

The probability that any given pair of firms form a tie is a function of the individual and joint attributes of those firms:

$$P[M_{ij} = 1] = G(X_i, X_j, \hat{X}_{ij}) \in [0, 1].$$

Because the net gains from tie formation are unobservable, this setting corresponds to a latent variable model in which there is an unobserved variable which represents the anticipated net gains (quality) of a tie. We assume that any pair of firms in the network will form a connection when the net gain from doing so is positive. We denote the net gains from the formation of a tie between firms i and j by Y_{ij} , so that $M_{ij} = 1_{Y_{ij} > 0}$. We further specify the gains function g so that $Y_{ij} = g(X_i, X_j, \hat{X}_{ij}) - \epsilon_{ij}$, where ϵ_{ij} is an independent, mean zero error term with cumulative density function F . Then

$$G(X_i, X_j, \hat{X}_{ij}) = P[M_{ij} = 1] = P[Y_{ij} > 0] = P[g(X_i, X_j, \hat{X}_{ij}) > \epsilon_{ij}] = F(g(X_i, X_j, \hat{X}_{ij})).$$

To simplify notation, we denote $g(X_i, X_j, \hat{X}_{ij})$ as $g(i, j)$ and $G(X_i, X_j, \hat{X}_{ij})$ as $G(i, j)$. Since ties are bi-directional in this model ($M_{ij} = M_{ji}$), g and G must be symmetric: $g(i, j) = g(j, i)$ and $G(i, j) = G(j, i)$. Given a set of binary bi-directional ties between firms, the gains function can be estimated via a standard logit or probit model. Also, since we do not observe the ultimate division of surplus, our model implicitly assumes that the *total* gains from tie formation are what drives the formation of a tie.

We can extend this framework to include the possibilities that ties may be of different strengths. To do so, we set M_{ij} to equal the number of interactions that underly a single link. Then $G(X_i, X_j, \hat{X}_{ij}) = \max(0, Y_{ij})$, and we identify the net gains from a given potential match from the number of ties rather than the existence of a tie, putting more weight on a link when it occurs more frequently. Given a set of weighted bi-directional ties between firms, the gains function can then be estimated using a Tobit regression.

In our tests, we will first estimate the determinants of the latent variable Y (the g function) to test theories of tie formation. This approach allows us to escape the problems inherent in inter-

preting effects of interaction terms and compound terms in probit and logit regressions described by Ai and Norton (2003). We will then use the marginal effects (the G function) to interpret the economic magnitudes of the determinants of tie formation.

We make three identifying assumptions in our estimation procedure. The first assumption is that higher quality matches have a higher propensity to be realized, and we believe this assumption is innocuous. The second assumption is that pair-tie-qualities are independent, or, put differently, that the firm-pair is the correct unit of observation, and the presence of a third firm does not change the propensity of the first two firms to tie. In other words, we are treating the group of three VC firms A-B-C as three pairs of VC firms: A-B, B-C, and A-C, and we assume that the presence of C does not affect the propensity of A and B to tie.⁴ This assumption does not prevent tactical formation of ties in the future—a tie between A and B may have value to B from anticipated future ties—as long as the basis for anticipated future ties can be proxied by current characteristics, such as network centrality or betweenness. Thus, our third assumption is that ties are formed based on information contained in current characteristics.

In order to disentangle cumulative advantage and similarity empirically, we also require that firms are sufficiently unconstrained in the number of ties that they can form. In a standard one-to-one matching model (e.g., Becker, 1973; Shimer and Smith, 2000), each partner is limited to *one* other partner. While each participant prefers the best available partner, the observed ties in equilibrium are between similar partners, despite the fact that firms formed such ties as a result of cumulative advantage motives. In contrast, if each partner could link with *many* others, partners with a high endowment of the resource in question will link with other highly endowed partners, but also will link with partners that have lower endowments of that resource once matches with highly endowed partners are exhausted. Since ties between two firms with a low endowment of the resource are the least valuable, they will be the least frequent. Thus, it is the desire to match with the best available partner *in combination with* capacity constraints that lead to similarity in outcomes in standard positive assortative matching. If capacity constraints are relaxed, one may observe a pattern of high-low links along with many high-type links, enabling the observer to separate cumulative advantage from similarity. Our empirical results (a lack of similarity-based matching; see Section 4) suggest that capacity constraints are not binding in our setting.

⁴For an approach that considers the formation of syndicate groups, see Bubna et al. (2014).

2.2 Specification and tests

For simplicity, we assume a linear structure on $g(i, j)$.⁵ Consider a pair of resources, A and B ; firm i 's holding of A is A_i and firm j 's holding of B is B_j . Our basic specification specifies that the gains from a tie will be determined by the quantity of resources available to the pair and the resource arrangement:

$$g(i, j) = \sum_{resources} \beta_S^A (A_i + A_j) + \beta_D^A |A_i - A_j| + \sum_{pairs} \beta_{RS}^{AB} [(A_i - A_j)(B_j - B_i)]^+ + \gamma Z_{ij}, \quad (1)$$

where Z are any additional controls (such as past shared investment sectors, etc.). ‘Pairs’ are unordered resource pairs, so four resources leads to six combinations. When we are discussing a generic resource, we will omit the superscript on β_S and β_D .

The first two terms test for the effects of the total level of any one resource across both firms ($A_i + A_j$) and its arrangement ($|A_i - A_j|$). A naive approach in the literature is to interpret $\beta_D < 0$ as evidence for similarity-based motives in tie formation; alternatively, a positive coefficient on an indicator variable for similarity along some dimension is interpreted as evidence of similarity-based matching. To test for cumulative advantage, a naive approach is to interpret $\beta_S > 0$ as evidence that firms use their ties to accumulate as much of a given resource as possible. However, neither of these two approaches is correct. To illustrate how these sums and differences interact, we consider a simple economy made up of two types of firms: High-type firms have one unit of resource A , low-type firms have zero units of A , and firms are identical along all other dimensions.

Both cumulative advantage and similarity-based matching predict that high types prefer to link with other high types over linking with low types: $g(H, H) - g(H, L) = \beta_S(1 + 1) + \beta_D|1 - 1| - \beta_S(1 + 0) - \beta_D|1 - 0| = \beta_S - \beta_D > 0$. Thus, to distinguish between the two hypotheses, we must examine the preferences of the low types. Similarity-based matching implies low types prefer other low types ($g(H, L) - g(L, L) = \beta_S + \beta_D < 0$), while cumulative advantage implies that low types prefer to match with high types ($g(H, L) - g(L, L) = \beta_S + \beta_D > 0$). A key point is that *both* similarity-based matching and cumulative advantage may lead to the observation of many ties between two high-type firms. The distinction is that similarity *also* predicts more ties between two

⁵For robustness, we consider alternative functional forms (such as squaring the difference terms). While doing so complicates the inference, we find that interpretation is largely unchanged.

low-type firms, whereas cumulative advantage predicts some mixing between high and low types.

It is also possible that firms prefer to match with partners that differ with respect to a particular resource level ('anti-similarity'). Anti-similarity may result, for example, if firms trade a particular pair of resources, as we may then observe differing levels of these resources for any given pair of firms. For low-type firms, anti-similarity and cumulative advantage have the same prediction that low-type firms will prefer to match with high-type firms ($g(H, L) - g(L, L) = \beta_S + \beta_D > 0$). However, anti-similarity implies high types prefer to match with low types rather than other high types ($g(H, H) - g(H, L) = \beta_S - \beta_D < 0$). We can therefore distinguish anti-similarity from cumulative advantage by examining the behavior of high types. To sum, the predictions of anti-similarity-based matching are the opposite of similarity-based matching.

Thus, we can reject hypotheses based on the signs of β_S and β_D alone, but sums and differences are required to confirm. For example, cumulative advantage implies $\beta_S - \beta_D > 0$ and $\beta_S + \beta_D > 0$. Adding these two equations together, we see that cumulative advantage implies $\beta_S > 0$, so $\beta_S \not\leq 0$ is sufficient to reject cumulative advantage. However, $\beta_S > 0$ alone is not sufficient to confirm cumulative advantage. Similarly, we can reject similarity-based matching if $\beta_D \not\leq 0$, but $\beta_D < 0$ is not sufficient to confirm. Distinguishing the various forms of matching requires tests of the *sums and differences* of coefficients on paired resources, rather than of each individual coefficient alone.

More generally, holding the levels of all other resources equal, we can take the derivative of the gains function (1) with respect to the resource levels of the two firms:

$$\left. \frac{\partial g(i, j)}{\partial A_i} \right|_{B_i=B_j} = \begin{cases} \beta_S + \beta_D & \text{if } A_i > A_j \\ \beta_S - \beta_D & \text{if } A_i < A_j \end{cases}.$$

Here, $\beta_S + \beta_D$ describes the effect of variation in the resource level of the firm with more of the resource, whereas $\beta_S - \beta_D$ describes the effect of variation in the resource level of the firm with less of the resource. Under cumulative advantage, increasing *either* potential partner's resource level increases the net gains from a potential match, and so we should observe both $\beta_S + \beta_D > 0$ and $\beta_S - \beta_D > 0$. In contrast, if similarity enhances the net gains from a potential match, increasing the resource level of the partner with less of the resource will increase the quality of a tie, while increasing the resource level of the partner with more will decrease the quality. Thus, we require $\beta_S + \beta_D < 0$ and $\beta_S - \beta_D > 0$.

To confirm our interpretation, observe that the specification in (1) is mechanically equivalent to

$$g(i, j) = \sum_{resources} \beta_{MAX}^A \max(A_i, A_j) + \beta_{MIN}^A \min(A_i, A_j) + \sum_{pairs} \beta_{RS}^{AB} [(A_i - A_j)(B_j - B_i)]^+ + \gamma Z_{ij}, \quad (2)$$

where $\beta_{MAX} = \beta_S + \beta_D$ and $\beta_{MIN} = \beta_S - \beta_D$.⁶ Cumulative advantage requires that the quality of a potential link increases in either firm's resource level, so that $\beta_{MAX} > 0$ and $\beta_{MIN} > 0$. Similarity-based matching requires that the quality of a potential link increases in the resource level of the smaller partner and decreases in the resource level of the larger partner: $\beta_{MAX} < 0$ and $\beta_{MIN} > 0$.

Finally, resource sharing motives imply that partnerships are driven by trade across resources. If both A and B are important inputs into the production function of the firm, two firms i and j are more likely to engage in shared activity (and thus form a tie) if one of the pair has a high endowment of resource A and little of resource B , and the other is endowed with a high level of B and little of A . Tests for resource sharing should therefore consider pairs of resources and focus on potential pairings in which the VC firms have resources to trade. A straightforward term for capturing this notion is $[(A_i - A_j)(B_j - B_i)]^+$. The $[X]^+$ notation is used to denote the positive component of X : $\max(X, 0)$. The max operator separates out those observations for which one firm has more of resource A and the other firm has more of resource B : $(A_i - A_j)(B_j - B_i) > 0$ when one firm, i or j , has more of one resource and less of the other. This structure identifies cases in which resource trading is possible. Under resource sharing, ties are of higher quality when the differences in resource levels are greater, and therefore, we would expect this term to have a positive effect on $g(i, j)$. In a linear specification, a sufficient test for resource trading motivations is thus $\beta_{RS} > 0$.

The presence of resource trading can also inform the importance of agency considerations (e.g., as in Casamatta and Haritchabalet, 2007; Cestone et al., 2007) beyond tests for similarity-based matching. Suppose two firms differ in their levels of a resource such as expertise, and a firm with

⁶The point estimates are mechanically equal for specifications (1) and (2). Standard errors that use a particular correlation structure, such as two-way clustering, may be different, however.

higher levels of expertise can hold up or expropriate a partner with less expertise. If agency costs are a first-order consideration in the selection of partners, expertise should not be traded for other resources, as such trade would imply that one of the partners who is trading is highly endowed with expertise (and less endowed with a different resource they are trading for) while the second partner is endowed with little expertise (but a high amount of the second resource that is being traded). More generally, we should not observe economic ties between firms with different levels of any type of resource if agency concerns are important for that resource: observed ties should be purely between similar firms. In contrast, if agency concerns are not primary, then we may observe high-expertise firms with low levels of capital co-investing with firms that have high levels of capital but low levels of expertise, for example. Thus, the relative frequency of similar pairs versus resource trading can shed light on the relative importance of agency problems.

Our predictions and the respective empirical tests are summarized in Fig. 1. We note that resource sharing, cumulative advantage, and similarity-based motives for ties need not be mutually exclusive. For example, one might imagine that firms match on certain resources based on cumulative advantage while seeking similarly endowed partners with regards to other resources that are more prone to lead to agency conflicts.

3 Data

The data for our analysis come from Thomson Financial’s Venture Economics database. Our sample, which is also employed in Hochberg et al. (2007), begins in 1980, marking the beginning of venture capital as an asset class that attracts institutional investors, and extends through 2003, with firm exit information updated through 2009.⁷ As many of our computed measures require five years of historical data, we include all VC investments made from 1975 onwards. We concentrate solely on U.S.-based VC investments, excluding investments by angels and buyout funds. While VC funds have a limited (usually ten-year) life, the VC management firms that manage the funds

⁷The institutionalization of the VC industry is commonly dated to three events: The Prudent Man interpretation of the 1978 Employee Retirement Income Security Act (ERISA) allowing pension funds to invest in higher-risk asset classes; the 1980 Small Business Investment Act which redefined VC fund managers as business development companies rather than investment advisers, lowering their regulatory burdens; and the 1980 ERISA Safe Harbor regulation, which sanctioned limited partnerships that are now the dominant organizational form in the industry. Venture Economics began compiling data on venture capital investments in 1977, and has since backfilled the data to the early 1960s. All data through the mid-2000s are verified for reporting VC firms through reports to limited partner investors.

have no predetermined lifespan. Success in a first-time fund often enables the VC firm to raise a follow-on fund (Kaplan and Schoar, 2005; Hochberg et al., 2014; Chung et al., 2012), resulting in a sequence of funds raised a few years apart. Experience and contacts acquired in the running of one fund carry over to the firm’s next fund and, therefore, we measure VC characteristics at the firm rather than fund level.

3.1 Ties

To construct the pattern of economic ties among VC firms, we follow Hochberg et al. (2007), and use co-investments in VC portfolio companies. As our analysis will focus on undirected ties, we define the syndicate as the collection of VC firms that invested in a given portfolio company across all rounds.⁸

We construct a new network of co-investment ties for each year t , using data on syndications from the five years ending in t . Within each of these five-year windows, we make no distinction between relationships reflected in earlier or later co-investments. We compute both binary networks that record a tie if VC i and VC j form one or more syndicates over the course of the five-year period, and valued networks that weight each tie between VC i and j by the number of companies in which they have co-invested over the five-year period, forming a count of the ties. Each of these is used as a dependent variable in our analysis.

In addition, we create four indicator variables for each VC-pair’s interactions in each five-year period: if the VC-firm-pair invested in the same industry segment; if the VC-firm-pair invested in the same geography segment; if the VC-firm-pair had a tie in the previous five years; and if each VC firm in the pair had a tie with a common third firm (i.e., were friends-of-friends).

3.2 VC firm characteristics

We compute a variety of VC firm-level characteristics. In Table 1, we present the number of observations, mean, and standard deviation for each of the VC firm characteristic measures presented below.

⁸While we do not present results in this paper, we observe similar patterns when analyzing ties in directed networks that distinguish the direction of ties from lead-investor to non-lead investor. There, we define links based on the collection of VC firms that invest in a given portfolio company investment round. The similarity of observed patterns for directed and undirected ties suggests that our findings are not dependent on one’s status as a lead or non-lead investor in the formation of the tie.

To measure the overall time in existence of the VC firm, we take the natural logarithm of the number of days since the VC firm’s first-ever investment. Additionally, we calculate VC time in existence on a per-sector basis. During the period of our sample, Venture Economics classifies investments into six broad industry sectors: Biotechnology; Communications and media; Computer-related; Medical, health, life sciences; Non-high-technology; and Semiconductors, other electronics. We calculate a VC firm’s duration in each sector as the natural logarithm of the number of days since the firm’s first-ever investment in that sector, to year t .

Many VC firms may focus their investments in a particular industry sector or geographic location (Sorenson and Stuart, 2001) or by stage of initial investment. We define three measures of VC firm specialization, each using the Herfindahl-Hirschman Index (HHI) of investment over the five-year period ($t-5$ to $t-1$) based on the dollar amount of investment. We compute specialization measures for industry using the six broad Venture Economics (VE) sectors, geography using Metropolitan Statistical Areas (MSAs), and stage (as defined by VE) using only the earliest round in which each firm invests for each portfolio company.⁹ To ease interpretation in our subsequent analysis, we transform these variables to obtain measures of generalization across industry, geography, and stage, defined as $1 - HHI(X)$.

The size of a VC firm, the extent of its investment activities, and the amount of capital it has available for investment may all influence its desirability as an investment partner. We construct a number of measures that capture the extent and size of a VC firm’s activity. In each year t , we compute VC firm assets under management as the sum of the total dollars committed to its currently active funds, where a fund is defined as active for ten years from its initial raising. We compute the total number of dollars invested by the firm, number of companies invested in by the firm, and number of investment rounds participated in by the firm over the period $t - 5$ to $t - 1$ as measures of overall extent of recent firm investment activity. We compute the VC’s ‘dry powder,’ or capital available for investment, as the total committed capital of its most recently raised fund minus the dollars already invested by that fund in portfolio companies by time t . To capture the typical size of deals in which the firm invests, we compute the average total round size for the investing syndicate for rounds of investment in which the VC firm participated over the period $t - 5$ to $t - 1$. We also compute the number of portfolio companies a VC firm has funded

⁹All reported results in this paper are robust to employing geography segment controls based on states.

and the fraction of the firm’s total deals that it originated (participated in the first round) since its inception. We further compute measures of the past success of a VC firm. Following common convention in the literature, we compute two measures of success: the VC firm’s historical IPO rate, defined as the proportion of its portfolio firm investments that have successfully exited via initial public offering (IPO), and the VC firm’s historical M&A rate, defined as the proportion of its portfolio firm investments that have successfully exited via trade sale, merger, or acquisition (M&A). As more recent exit activity may be more salient, we additionally compute the number of IPOs and the number of M&A exits the firm has had over the preceding five-year period.

Finally, Gulati (1998, 1999) suggests that current network position can influence the future formation of ties. We utilize five measures of the VC’s current network position, each of which captures a slightly different aspect of a VC firm’s influence in the network. We compute the VC firm’s *degree* as the number of unique VCs in the network with which a VC has ties, normalized by the maximum possible degree for that size network (i.e., $n - 1$), as a proxy for the information, deal flow, expertise, and contacts to which it has access. We compute *indegree* as the number of unique VCs in the network who have invited the VC firm in question to join them in a syndicate as a junior co-investor, thereby expanding its investment opportunity set, and *outdegree* as the number of unique VC firms in the network that the VC firm in question has invited into syndicates it has led, which captures the VC firm’s ability to generate such co-investment opportunities. As with the previous measure, both *indegree* and *outdegree* are normalized by the maximum possible measure obtainable in a network of that size. We compute *eigenvector centrality* as the sum of a VC firm’s ties to other VCs, weighted by their respective centralities, and normalized by the highest possible eigenvector centrality in a network of that size. This captures a VC’s access to the best-connected VCs. Last, we compute *betweenness*, which captures a firm’s ability to act as an intermediary in bringing together VCs for investment opportunities, as the proportion of all paths in the network linking any two other VCs in the network that pass through the VC firm, normalized by the maximum betweenness for a network of that size.

3.3 Characterizing resource factors

Many VC firm characteristics likely measure aspects of the same underlying feature of the firm, making it difficult to interpret empirical models that employ all observable characteristics as in-

dependent variables. We employ a factor analysis to extract the main variation in the VC firms' characteristics. Factor analysis reduces the attribute space from a larger number of variables to a smaller number of latent factors. Further, the factors can be specified to be orthogonal to one another.¹⁰

Our factor analysis uses as inputs all of the VC firm characteristics described in Section 3.2. Table 2 reports the results of the factor analysis, with orthogonal factors of mean zero and standard deviation one. Factors are expressed as loadings on the characteristics. A factor's eigenvalue is a measure of the amount of information captured by the factor. A standard criterion is to include all factors with eigenvalues greater than one—meaning all factors that in some sense have more information than the average variable. The first four factors have eigenvalues greater than one and cumulatively explain approximately 95% of the variation in the VC characteristics variables. The fifth factor produced in the rotated analysis has an eigenvalue of 0.56.

These factors also have natural interpretations. The first factor has an eigenvalue of 10.71 and can be interpreted as an *experience* factor. The characteristics with the highest loadings on this factor are the VC firm's overall experience and the six sector-specific experience variables, with rotated loadings ranging from 0.67 for experience in the biotechnology sector to 0.93 for general VC firm experience. The total number of companies in which the firm has invested and its recent round activity load moderately, with loadings of 0.53 and 0.49. The set of variables with the next highest loadings in this factor are variables related to past investment success: the historical exit rate, historical IPO rate, recent IPOs, and recent M&A exits have loadings that are considerably lower, ranging from 0.3 to 0.4.

The second factor, with an eigenvalue of 3.70, can be interpreted as an *access* factor. The characteristics with the highest loadings on this factor are the five normalized measures of network position (normalized degree, indegree, outdegree, eigenvector centrality, and betweenness), with rotated loadings ranging from 0.73 for betweenness to 0.95 for degree. Additionally, the number of companies in which the VC firm has invested over the preceding five-year period has a loading of 0.67. Recent IPO activity loads moderately, at 0.54. This likely captures the VC firm's portfolio company network reach, and thus perhaps the firm's more general network access.

¹⁰For the clearest interpretation of the factors, we use the orthogonal varimax rotation of Kaiser (1958), which maximizes the variance of the squared, normalized characteristic loadings within a factor. See also Jolliffe (2004) for a discussion of factor analysis and Kaplan et al. (2012) for an application to CEO characteristics.

The third factor, with an eigenvalue of 2.08, can be interpreted as capturing *available capital*. The characteristics with the highest loadings on this factor are assets under management, the total dollars the VC firm has invested over the prior five years, and the measure of ‘dry powder,’ or uninvested capital, with rotated loadings ranging from 0.70 for dry powder to 0.90 for assets under management.

Finally, the fourth factor has an eigenvalue of 1.32, and can be interpreted as an *investment scope* factor. The characteristics with the highest loadings on this factor are the three measures of generalization along industry, geography, and stage, with rotated loadings ranging from 0.75 for industry scope to 0.78 for geographic scope.

We note that a number of the included characteristics do not load strongly on any of the factors. These include the fraction of deals that the firm originates, average round size, and, to a lesser extent, historical and recent exit rates. To our knowledge, there is no formal method for determining whether to consider a factor as representative of a particular attribute. In our analysis, the largest break in loadings across all factors occurs between the 0.67 loading on recent number of companies and the 0.54 loading on recent IPO activity, both for the access factor. In providing intuition about the magnitudes of effects, we take this break as determining whether a factor represents a particular attribute. All of our tests, however, consider the full vector of factor loadings.

In Panel B of Table 2, we present scoring coefficients used to determine resource factors for each VC-year. While the loadings (discussed above) describe how to recover characteristics from factors, the scoring coefficients describe how to recover factors from the observed characteristics. Scores are obtained using the regression method, with coefficient weights computed by multiplying the inverse of the observed variable correlation matrix by the matrix of factor loadings. To calculate a particular VC’s resource endowment, we multiply the scoring coefficients by the standardized values of observed characteristics and take the sum.

To further the intuition for the resource factors, we relate them both to partnership performance and to the breadth and depth of a VC firm’s co-investment ties over the subsequent period. In untabulated results, we estimate fractional logit models of IPO and exit rates as a function of the four resource factors.¹¹ We also estimate probit and Tobit models relating a firm’s four factor

¹¹The fractional logit model, proposed by Papke and Wooldridge (1996), is a general linear model with a binomial distribution and a logit link function. This approach allows us to use zeros and ones, as well as intermediate proportions, with a logit transformation of the dependent variable.

resources to the firm’s likelihood of forming any tie, the proportion of the VC firms in the network with which it ties, and the strength (i.e., number) of ties formed. The models include year indicators, with robust heteroskedasticity-consistent standard errors clustered at the VC-firm level.

The estimates from these models suggest that experience, access, and scope are positively related to VC performance as measured by the proportion of successful exits. This result is consistent with our interpretation of these factors as value-added resources. In addition, higher-access, better-capitalized, and more broadly focused firms are more likely to form any tie, tie with a larger number of distinct partners in the network, and form stronger and more stable ties. Experience, in contrast, is associated with fewer, weaker ties: it exhibits no significant effect on the likelihood of having a tie in the network and is negatively and significantly related to the number of VC firms with which a given firm ties and the strength of those ties. Already, we observe that not all resource factors behave similarly in predicting either success or the formation of ties.

4 Empirical analysis

For our analysis, we estimate the likelihood of a tie existing between a pair of VC firms as a function of the resource profiles of the two firms in question using the model described in Eq. (1). The unit of observation is a pair of VC firms in a given year, constructed using data over a five-year period.¹² In each specification, we include eight single-resource terms: for each of the four resource factors, there is a summation term and an absolute difference term describing the resources of the pair. We include six dual-resource terms to capture resource trading, representing the $\binom{4}{2} = 6$ pairs of distinct resources.

The estimates from our models are presented in Tables 3 and 4. Table 3 presents an estimation of the model that includes only the single-resource terms. Table 4 adds the resource trading terms to the model. For both tables, Panel A presents the results of the estimation, and Panel B presents the *t*-tests for the hypotheses of cumulative advantage and similarity-based matching described in Section 2. Fig. 2 summarizes the results of the hypothesis tests for both tables to ease interpretation and comparison.

We begin by examining the formation of undirected, binary ties. Thus, the dependent variable

¹²Our results throughout the paper are robust to estimating reduced panel models that include only non-overlapping periods rather than rolling five-year periods.

in each column 1 takes the value of one if the pair (VC i , VC j) form a tie over the five-year period t to $t + 4$, and zero otherwise. The models are estimated using probit regressions, with robust, heteroskedasticity-consistent standard errors two-way clustered by VC firm. As an alternative, we also compute standard errors clustered by VC pair and bootstrapped standard errors; results are similar. Two-way clustering produces the most conservative standard error estimates of the methods employed, and as such are reported in the tables throughout.

In column 2, we replace our binary measure of ties with the valued measure that captures the strength of the tie between VC i and j if such ties exists, and zero otherwise, and we estimate a Tobit model. In columns 3 and 4, we re-estimate the baseline models from columns 1 and 2, adding indicator controls for whether the pair of VC firms in question had previously invested in a common geography or industry segment. In all specifications of Tables 3 and 4, we also include indicator variables for each year.

Across all four specifications in each table, we observe that the coefficients on the summed factors for access, capital, and investment scope are positive and significant, as are coefficients for the absolute value of differences in the experience factor. The difference factor coefficients for access and capital are negative and significant. As previously noted, on their own, the signs and significance of the coefficients tell us very little about the nature of the ties. Instead, we focus on the relation between the coefficients for the sum and absolute difference coefficients for each of the individual resource factors.

We first consider tests for similarity-based matching and cumulative advantage motives. The patterns we describe below are apparent regardless of whether we estimate the model with or without the resource sharing terms. First, recall that if firms seek similarity in a particular resource, we expect $\beta_S + \beta_D$ (the coefficient on the summed resource levels of firm i and firm j plus the coefficient on the absolute differences of the resource level of firm i and the resource level of firm j) to be negative, while we expect $\beta_S - \beta_D$ to be positive. For the experience factor, the first of these predictions is violated in the baseline model ($\beta_S + \beta_D$ is positive) and the second is inconclusive ($\beta_S - \beta_D$ is insignificantly different from zero); both of these predictions are violated in the models controlling for past shared investment location or industry ($\beta_S + \beta_D$ positive and $\beta_S - \beta_D$ negative). These results suggest that the motive for matching on experience is not similarity-based. Furthermore, only one of the two conditions for cumulative advantage on experience is met:

$\beta_S + \beta_D$ is positive, as predicted by cumulative advantage, but $\beta_S - \beta_D$ is negative (or zero), where cumulative advantage would predict it positive as well. Thus, neither similarity-based matching nor cumulative advantage appear to be supported for formation of ties on the experience factor; rather, the coefficients for the experience factor terms are consistent with anti-similarity. In contrast, we find clear support for cumulative advantage for the access and investment scope factors, with both conditions for cumulative advantage met for each, and the $\beta_S + \beta_D < 0$ condition for similarity-based matching violated.

The tests for the capital availability factor are more nuanced. From Eq. (2), the sum $\beta_S + \beta_D$ gives the effect of increasing capital availability for the partner that has more capital. The sum $\beta_S - \beta_D$ does the same for the partner that has less capital. Since $\beta_S + \beta_D$ is near zero and not significant, while $\beta_S - \beta_D$ is large and significant, our estimates imply that ties are more likely when the partner with less capital has more, but not when the partner with more capital has more. From Fig. 1, this outcome would ensue when cumulative advantage and similarity-based matching both exist at roughly the same magnitude.¹³

We now turn to the resource sharing terms in the model. The test for resource sharing is that the coefficient β_{RS} for a pair of resources be positive. Examining the estimate summary in Fig. 2 indicates a number of resource pairs that appear to be traded. The coefficient of interest, β_{RS} , is *positive* and significant for the pairs (experience, available capital) and (investment scope, available capital) in all specifications, and additionally for the pair (access, available capital) in the models that control for past shared investment location and industry. Thus, VC firm i 's availability of capital appears to trade with firm j 's experience, investment scope, and access. In contrast, β_{RS} is *negative* and significant for the pairs (access, experience) and (access, investment scope), suggesting that the gains from trade are higher when the firms in the pair are not trading these resources, but rather, only one firm of the pair is highly endowed with both resources. The combination of the positive β_{RSS} for capital availability vis-a-vis experience, investment scope, and access and the negative β_{RSS} for access vis-a-vis experience and investment scope suggests formation of a tie between two VC firms is especially beneficial when one of the pair is endowed with high levels of

¹³Strictly speaking, we cannot confirm the presence of either cumulative advantage or similarity for the capital factor since the sums of the coefficients are not measurably different than zero. However, because the magnitude of the difference in coefficients is so large—consistent with both motives—we choose the interpretation of both effects being present, but in tension.

experience, access, and investment scope, and low levels of capital availability, while the other is endowed with low levels of skill, access, and scope, but high levels of capital. In industry parlance, this can be interpreted as the equivalent of ‘high value-added’ pairing with ‘dumb money.’

A natural question is whether observing higher gains for ‘high value-added’ firms forming ties with ‘dumb money’ might be an artifact of measuring ties using all rounds of investment. Common belief among VC practitioners is that investors often bring in syndicate partners that have high capital availability in later rounds of investment, while experience, networks, or other expertise may be more beneficial in earlier rounds of investment. For robustness, in unreported results, we reformulate our networks such that a VC-firm-pair has a network tie only if they have co-invested in one or more first-round deals; we then re-estimate our models using the measures of ties that result from these first-round co-investments. We observe qualitatively similar patterns for both the one-resource and two-resource tests, suggesting that the patterns of resource combination and distribution over tie formation are also present for first-round investment ties.

Our findings on trade are more intuitive than they may perhaps seem: for certain deals, high-value-added VC firms may prefer to avoid syndicate conflicts that can arise from partnering with another high-value-added VC whose opinions may differ from theirs but who may believe that their signal is the correct one. They may therefore partner with low-value-added, potentially passive, VC firms who are likely to let them set strategy for the syndicate. Along this same line, it is possible that organizations with large amounts of capital but less in the way of value-added resources are more likely to rely on the signal of the high-value-added resource investor rather than seeking their own signal, thus reducing coordination costs. This interpretation is consistent with the findings of Brander et al. (2004), who report evidence against the second-opinion hypothesis as a motive for syndication.

One might think access and perhaps scope are more likely to be developed over time if a VC firm has a preference for tying in general. While our goal is to describe patterns of observed tie formation as related to existing characteristics, in unreported tests we augment our models with a control for the total number of ties for both VC firms in the pair and also estimate alternative specifications that include a fixed effect for the level of pair ties. These tests also serve to assuage concerns over VC firms facing some form of loose capacity constraint for ties. Given the high correlation between the access resource factor and ties, some coefficients are unsurprisingly weakened. Nevertheless,

the pattern of resource combination and distribution remains qualitatively similar.

4.1 Robustness: Past ties and indirect ties

Thus far, the patterns we observe are consistent for both binary and valued measures of pair-level ties, both with and without controls for similar areas of investment as proxied by geography or industry. Because the networks we explore are based on co-investment activities, the VC firms involved in the relationship presumably evaluate their partner and may build partner-specific capital. Once the relationship is formed, such costs are sunk, but VCs gain additional information about partner quality. Thus, it is natural to ask whether initial tie formation and tie continuation manifest of the same process.

We can test for the role of past ties either by including an additional control or by separating the sample into VC-pairs that have a previous tie and VC-pairs that do not. Separating the sample allows us to test for different patterns of network formation without having to specify a functional form for the difference. Table 5 presents the results for the subsample of VC-pairs for which there existed a tie in the prior five-year period, and the subsample of pairs for which no prior tie existed between the two. We estimate both models for existence of a tie and for the strength of ties. The table presents estimates from our baseline models (including resource sharing terms) when run on the two subsamples; all of our results are robust to controlling for whether the pair in question had, in the immediate prior period, invested in the same industry segment or same geography segment (MSA).¹⁴

Fig. 3 summarizes the results in Table 5. The subsample results are broadly similar to the main results, with two important differences. First, the access for capital trade is statistically significant only for repeat ties. Second, experience does not have a statistically significant impact on repeat ties and the statistical significance of investment scope is less. One interpretation for these differences is a fixed assets effect: once formed, relationships may persist even if the characteristics of the underlying firms change, and this effect may drive coefficients to zero. In particular, as opposed to access, scope, or capital, which may or may not change over time, experience *must*

¹⁴As the existence of a prior tie between the VC-pair implies a past shared investment and thus that both members of the pair had previously invested in the same industry and geography segment, we include the past investment in same industry or geography segment controls only in the models estimated on the subsample of pairs with no ties in the prior period.

necessarily change for firms as they move from one five-year period to the next. For the resource sharing terms, we observe far less resource sharing than in the full sample, and no negative resource sharing. Here, capital trades with experience only in the specification for the valued tie measure, though it continues, as in the full sample, to trade with access in both specifications. In contrast to the full sample, we see no negative resource sharing on the pairs (capital availability, access) and (access, investment scope), suggesting that the ‘smart skills/dumb money’ trade is not a significant driver of tie formation when a tie between the parties existed in a previous time period. As with the single-resource patterns, we can interpret the differences between the results for the repeat ties subsample as consistent with relationships being fixed assets for firms with changing characteristics over time.

Next, it is reasonable to posit that tie formation may be facilitated by the underlying organizational social network formed by co-investment activities. For example, forming ties based on indirect network ties, e.g., with a friend of a friend, might play a role. We test for the role of indirect network formation by examining the subsample of VC-pairs that are indirectly linked (friends-of-friends), and the subsample of VC-firm-pairs that do not share an indirect link. Table 6 presents estimates of the models for tie existence and tie strength for the subsample of VC-firm-pairs that have indirect ties, and those that do not. As in previous analysis, all of our estimated results are robust to the inclusion of the controls for both VCs in the pair having previously invested in the same industry or geography segment.

Fig. 4 summarizes the one- and two-resource hypothesis tests. The patterns of network formation for indirectly linked VC-firm-pairs (friends-of-friends) are qualitatively similar to those observed in the full sample. One difference is that matching on the experience factor, while still taking the form of anti-similarity, differs across the two subsamples. In the friends-of-friends subsample, matches are more frequent when the stronger (i.e., more experienced) of the two firms in the pair gets even stronger, whereas in the not friends-of-friends subsample, matches are less frequent when the weaker (i.e., less experienced) of the two firms in the pair gets even weaker. The full sample had both effects. For the resource sharing terms, we observe not only the patterns evident in the full sample, but also the addition of significant negative resource sharing between experience and investment scope among firms without indirect ties, lending further support to the

‘smart skills trade for dumb money’ interpretation of the full-sample estimates.¹⁵

4.2 Interpretation and discussion

In the description of the empirical estimates above, we deferred discussion of relative magnitudes for the effects on the latent gains function and associated probabilities. To more concretely translate factors and observable characteristics to outcomes, in this section we evaluate the effects of varying factor endowments and of varying the observable characteristics underlying the factor analysis on the probability of pairing.

We begin by comparing the probability of a pairing between two VCs with average endowments of each factor to pairings in which we vary a particular factor by one standard deviation for one of the VCs in the pair. Based on the estimates in Table 4, column 1, the probability of two average VCs pairing is 14.51%. Column 1 of Table 7 reports the probability of a VC with a single factor endowment reduced by one standard deviation and average endowments across all other factors pairing with a VC with average endowments across all factors. Column 2 reports the probability of a VC with a single factor endowment increased by one standard deviation and average endowments across all other factors pairing with a VC with average endowments across all factors. Since the two VCs in the pair will have the same average endowments in three of the four factors, the resource sharing terms will not affect the probabilities.

As discussed previously, the experience resource appears to enhance ties between dissimilar partners (anti-similarity). Thus, reducing the endowment of experience for the lower-endowed of the pair increases the probability of pairing slightly (the one-standard deviation reduction in the experience factor changes the probability of the pairing to 15.27%), as does raising the endowment of the more highly endowed of the pair (the one-standard deviation increase changes the probability of the pairing to 16.32%). The overall effect of having one VC of the pair move from a low endowment (minus one standard deviation) to a high endowment of experience (plus one standard deviation) is modest, an increase of approximately one percentage point.

In contrast, access and scope both exhibit traits indicative of cumulative advantage. Lowering

¹⁵In untabulated results, we estimate whether there is a significant *level*-effect relationship between the existence of a past tie or indirect tie and the gains from forming a tie for the full sample by including a control for the existence of a past tie (or tie strength) and a control for the existence of an indirect tie. The existence of such past or indirect ties does indeed have a positive and significant level relationship to the gains from forming a tie in the current period, and the general pattern underlying tie formation remains.

the endowment of either of these resources for one of the VCs in the pairing reduces the probability of a match substantially (to 5.68% and 10.69%, respectively), and increasing the endowment increases the probability (to 20.89% and 18.8%, respectively). Recall that the single-resource estimates suggest that the capital factor exhibits evidence of a tension between cumulative advantage and similarity-based matching. From the probabilities in Table 7, we see that when lowering the capital endowment of a VC in the pair the probability of pairing decreases dramatically to 2.92%, whereas increasing the endowment leaves the probability of a pairing with an averagely endowed VC virtually unchanged.

In columns 4 through 6 we perform similar computations, but rather than varying the factor endowments, we instead vary the (normalized) observable characteristics that load strongly for each factor by one standard deviation. All other characteristics for these (hypothetical) VCs are held at the sample mean. For this calculation, we consider factors with loadings (Table 2) of 0.66 and above as strong, corresponding to a natural break in our observed loadings. For robustness, we consider other thresholds such as 0.5 and 0.7 and obtain qualitatively similar results. To provide a more direct comparison to variation in the factors, we include only the single-resource effects in the calculation. Because many of these observable characteristics are correlated, the realized values for all factors change as we vary the characteristics for each single factor’s primary characteristics. For example, because proxies for experience (e.g., age) and proxies for access (e.g., centrality) are *positively* correlated in-sample but the underlying factors are orthogonal, increasing proxies for experience and holding other observables constant will increase the experience factor but *decrease* the access factor. This in turn will affect the gains function and probability of a pairing not only through an increased experience endowment, but also through a reduced access endowment. Since the coefficient estimates on terms for the access factor are many times greater than those for the experience factor, the net effect of varying characteristics related to time-in-existence may be related more to a decrease in the access factor rather than an increase in experience factor.

As seen in Table 7, varying the characteristics that load on the experience factor results in an increase in the probability of pairing when reducing endowments by one standard deviation, just as it did when reducing the factor itself by one standard deviation. However, the probability is also reduced when endowments relating to time-in-existence are all increased by one standard deviation, resulting in a negative overall change. This makes sense given the strong effects of

cumulative advantage for access (and scope). Also, varying characteristics relating to scope leads to a smaller predicted change in probability relative to what happens when we vary the scope factor itself. This is driven by a similar reduction in the access endowment.¹⁶

To gauge magnitudes of the effects on the latent gains function and associated probabilities from resource trading, we construct hypothetical VCs for each factor-pair evaluated less one standard deviation and plus one standard deviation from the mean, with average endowments in the other two factors. For each resource pair, we consider the magnitude of the gains from trade between two VCs, with the first VC having a lower endowment on one factor and a higher endowment on the other and the other VC endowed in the reverse. As before, we also perform the computations varying characteristics that load on each factor rather than factor levels themselves, with similar results.

To better understand and isolate the effects of trade, we illustrate with an example the *joint* role of single-resource endowments and the capital sharing result implied by the resource pair tests. Consider the gains from tying for two VCs with differing endowments in capital and experience. Using the results in Table 4 and substituting zeroes for statistically insignificant coefficients for illustration purposes (and recalling that $\beta_{MAX} = \beta_S + \beta_D$ and $\beta_{MIN} = \beta_S - \beta_D$), we have:

$$\begin{aligned} g(i, j) = & 0.078 \times \max(E_i, E_j) + 0 \times \min(E_i, E_j) \\ & + 0 \times \max(C_i, C_j) + 0.8834 \times \min(C_i, C_j) \\ & + 0.0978[(E_i - E_j)(C_j - C_i)]^+ + \{\text{other terms}\}, \end{aligned}$$

where E is the experience factor and C is the capital factor. Since the factors are normalized to be mean zero and standard deviation one, we examine $E_i = C_j = -1$ and $E_j = C_i = 1$.

Consider first the direct effects of experience and capital as single resources, as discussed above. Because j is more experienced, gains are higher by 0.078; because i is less experienced, gains are lower by 0; the net *direct* effect of experience is +0.078. Because i has more capital, gains are higher by 0; because j has less capital, gains are lower by 0.8834; the net *direct* effect of capital is -0.8834 . As previously discussed, both of these changes reflect cumulative advantage: gains

¹⁶The general pattern of the strongest increases in gains resulting from an increase in the scope and access factors is observed across most specifications.

are higher because one firm has more experience and lower because one firm has less capital. Because the capital effect is so much larger than the experience effect, gains from the pairing as a whole are lower by $0.078 - 0.8834 = -0.8054$. Now we examine the resource sharing effect. Since $[(E_i - E_j)(C_j - C_i)]^+ = 4$, gains increase by $0.0978 \times 4 = 0.3912$. This effect is larger than the direct effect of experience but smaller than the direct effect of capital. The resource sharing effect is both economically meaningful and positive while, *simultaneously*, firms whose resource endowments are such that they might trade capital and experience have a lower propensity to match than two firms both with endowments equal to the mean.

Computations for the resource pairs are tabulated in Panel B of Table 7. We also include computations for the pairing of a VC with a high endowment in all of the value-added resources and a low endowment of capital with a VC endowed in the reverse (i.e., having high levels of available capital and low levels of the three value-added resources). In the absence of resource sharing, varying the endowments of resources as described above results in a lower probability of a match between two VC firms relative to two average VC firms, for all resource pairs except experience/scope. To gauge the economic significance of resource trading, therefore, we compare the probability of a pairing between VCs implied by the full model with a base case for which resource sharing coefficients are zero.

For the VC-pair differently endowed with experience and capital, the probability of a match is 3.62% if we consider only single-resource effects. Once the effects of trade are considered, the probability increases to 7.54%. The effects of capital trading with scope are also influential, with an increase in probability from 2.75% based on direct effects only, to 4% with the full model. Potential trade among value-added resource pairs decreases the probability of a match, with the (experience/access) pair reducing the probability from 11% to 7.47%, and (access/scope) reducing the probability from 8.87% to 8.29%. When we consider variation in observable characteristics instead of factors, the changes are enhanced but similar in magnitude. For a high-value-added, low-capital VC matching with ‘dumb money,’ the probability climbs from 1.84% (0.76%) from direct effects alone to 4.21% (3.19%) with resource sharing when we vary the resource factors (underlying characteristics). Conditional on resource endowments, there is a substantial role for trade.

In sum, we see little evidence that the preference for resource similarity is a primary driver of

ties in the VC network. This finding suggests that agency considerations may not be first-order in determining which partners are selected by a VC firm from the network. This finding also stands in stark contrast to the large literature describing social networks, in which people tend to form ties with people who are similar to them (McPherson et al., 2001).¹⁷ Further, the lack of similarity-based matching implies that capacity constraints are not binding in this setting. Rather, we see evidence that in forming economic ties, VC firms on the one hand appear to gain most from ties with partner firms who are highly endowed with access and investment scope, regardless of the firm’s own endowment of these resources, and exhibit anti-similarity tendencies in choosing partners on endowments of experience. Our findings support theoretical arguments that partnerships may be formed to accumulate higher levels of resources required by the production function. The only evidence of a preference for similarity is in the formation of ties across the capital availability resource, though this too exhibits a tension with simply preferring a more-highly endowed partner. Finally, VC firms appear to gain most from trade when one firm is highly endowed in value-added abilities and the other has a high endowment of capital availability, again supporting the notion of resource accumulation.

5 Conclusion

In this paper, we develop a rigorous methodology to infer the underlying motives for the formation of ties between particular sets of partners in a network, thus informing the relative importance of agency cost and resource accumulation considerations in the formation of economic ties. To the best of our knowledge, our work provides the first formalized tests to disentangle existing underlying economic explanations for organizational tie formation.

Our methodology builds an empirical model of the gains from forming a tie between two firms. Using the assumption that ties are most likely formed when the anticipated net gains from doing so are higher, we employ latent variable models to study the economic drivers of network tie formation across organizations. With venture capital syndication networks as our test setting, we employ factor analysis to extract the main patterns of variation in firm characteristics and identify

¹⁷To date, the social networks literature has not incorporated methodologies that allow for correlated attributes and the possibility of gains from trade; trading of resources, however, is likely less important in the social networks setting as compared to the organizational networks setting of this paper.

a set of resources for our analysis. We find four significant, orthogonal resource factors, all of which have intuitive interpretations: experience, access, capital availability, and investment scope.

Overall, our findings suggest that concerns over agency conflicts are not a primary concern in the formation of VC syndication networks, as we find little evidence of preferences for similarity as the primary driver of partnership formation. Instead, these concerns appear to be dominated by a desire for resource accumulation.

While we find that firms do appear to trade resources in forming economic ties in the co-investment network, such resource sharing is not generic: capital availability appears to trade with experience and access, but resources related to the value-added capacity of the VC do not appear to be traded for one another. Rather, we find that a particularly beneficial trade is a tie formed between one firm who is endowed with high levels of all of experience, access, and investment scope, and a second firm who is endowed with little of these resources, but high levels of capital availability. Thus, capital can exist outside the firm and be combined effectively with inside expertise or value-added, but the same does not apply to combinations of inside-the-firm and outside-the-firm value-added resources.

Our work opens some interesting questions and avenues for future research. First and foremost is whether the patterns we identify generalize to other economic networks, particularly in settings where interactions are less frequent and less likely to be repeated (and thus, where agency concerns may be more influential). Second, the motivations typically ascribed to the formation of ties in organizational settings may also be relevant in social networks. Future research analyzing social ties which considers the competing influences we identify would be useful. Finally, our approach of employing factor analysis to capture orthogonal resources suggests a solution to the standard problem of making inferences on loose proxies for an underlying characteristic of interest. In research areas where multiple characteristics of an economic actor may actually be reflections of a more fundamental unobservable attribute (such as ‘quality’ for a VC firm), the extent to which existing conclusions are robust to the use of orthogonalized attributes or factors is an area for further exploration.

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Theory	Single resource	
	Prediction	Test
Similarity-based matching	$\left. \frac{\partial g(i, j)}{\partial A_i} \right _{B_i=B_j} \begin{cases} < 0 & \text{if } A_i > A_j \\ > 0 & \text{if } A_i < A_j \end{cases}$	$\beta_S + \beta_D < 0$ $\beta_S - \beta_D > 0$
Anti-similarity-based matching	$\left. \frac{\partial g(i, j)}{\partial A_i} \right _{B_i=B_j} \begin{cases} > 0 & \text{if } A_i > A_j \\ < 0 & \text{if } A_i < A_j \end{cases}$	$\beta_S + \beta_D > 0$ $\beta_S - \beta_D < 0$
Cumulative advantage	$\left. \frac{\partial g(i, j)}{\partial A_i} \right _{B_i=B_j} \begin{cases} > 0 & \text{if } A_i > A_j \\ > 0 & \text{if } A_i < A_j \end{cases}$	$\beta_S + \beta_D > 0$ $\beta_S - \beta_D > 0$
Theory	Resource pairs	
	Prediction	Test
Resource sharing	$\frac{\partial g(i, j)}{\partial [(A_i - A_j)(B_j - B_i)]^+} > 0$	$\beta_{RS} > 0$

Fig. 1. The figure presents predictions and tests on Eq. (1) from the three theories of syndication. $g(i, j)$ is the gains from syndication between firms i and j , while A and B are resources, such as capital or experience. $\beta_S + \beta_D$ measures the effect of an increase in the resource level of the potential partner with a greater level of the resource; $\beta_S - \beta_D$ measures the effect of an increase in the resource level of the potential partner with a lower level of the resource; β_{RS} measures the effect of an increase in the cross-difference of the resource levels.

Sample	Experience		Access		Capital		Investment scope	
	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$
Full - Probit w/o RS	+	—	+	+	0	+	+	+
Full - Tobit w/o RS	+	—	+	+	0	+	+	+
Full - Probit	+	—	+	+	0	+	+	+
Full - Tobit	+	—	+	+	0	+	+	+
Interpretation	Anti-similarity		Cumulative adv.		Cum. adv. & sim.		Cumulative adv.	

Sample	Resource sharing				
	Exp-Access	Exp-Capital	Exp-Scope	Access-Capital	Access-Scope
Full - Probit	—	+	0	+	—
Full - Tobit	—	+	0	+	—

Fig. 2. Summary of hypothesis tests for the full sample (from Tables 3 and 4), including geography and industry controls. The first two rows ‘w/o RS’ do not include the resource sharing terms.

Sample	Experience		Access		Capital		Investment scope	
	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$
Repeat ties - Probit	0	0	+	+	0	+	+	+
Repeat ties - Tobit	0	0	+	+	0	+	+	0
New ties - Probit	+	-	+	+	0	+	+	+
New ties - Tobit	+	-	+	+	0	+	+	+
Interpretation	Anti-similarity		Cumulative adv.		Cum. adv. & sim.		Cumulative adv.	

Sample	Resource sharing					
	Exp-Access	Exp-Capital	Exp-Scope	Access-Capital	Access-Scope	Capital-Scope
Repeat ties - Probit	0	0	0	+	0	0
Repeat ties - Tobit	0	+	0	+	0	0
New ties - Probit	-	+	0	0	-	0
New ties - Tobit	-	+	0	0	-	0

Fig. 3. Summary of hypothesis tests for repeat ties and new ties subsamples (from Table 5).

Sample	Experience		Access		Capital		Investment scope	
	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$	$\beta_S + \beta_D$	$\beta_S - \beta_D$
Friend-of-friends - Probit	+	0	+	+	0	+	+	+
Friend-of-friends - Tobit	+	0	+	+	0	+	+	+
Not friend-of-friends - Probit	0	-	+	+	0	+	+	+
Not friend-of-friends - Tobit	0	-	+	+	0	+	+	+
Interpretation	Anti-similarity		Cumulative adv.		Cum. adv. & sim.		Cumulative adv.	

Sample	Resource sharing					
	Exp-Access	Exp-Capital	Exp-Scope	Access-Capital	Access-Scope	Capital-Scope
Friend-of-friends - Probit	-	+	0	+	-	0
Friend-of-friends - Tobit	-	+	0	+	-	0
Not friend-of-friends - Probit	-	+	-	+	-	+
Not friend-of-friends - Tobit	-	+	-	+	-	+

Fig. 4. Summary of hypothesis tests for friend-of-friend and stranger subsamples (from Table 6).