

**Binding Conflict:
The Competition-to-Cooperation Switch in Firm Dyads¹**

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ABSTRACT

The Parsonian wisdom that social conflict has dissociating and disruptive effects guides the thinking of many students of economy. It leads them to believe that economic competition and cooperation are “polar opposites” and, consequently, competition between firms should hinder cooperation between them. I challenge the applicability of this intuitively appealing wisdom to economic life. My analysis of investment syndicates in venture capital industry demonstrates that the likelihood of cooperation between two firms is significantly and positively related to the intensity of competition between these firms in the preceding period. The likely mechanism leading to this outcome is the familiarity and knowledge-based trust, which both are greater between competitors than between non-competitors or two randomly selected actors.

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INTRODUCTION

It was the heyday of Parsonian functionalism when Lewis Coser published his *Functions of Social Conflict* (1956). Coser saw the mission of this book in demonstrating that Parsons's view of social conflict as a nuisance that society must get rid of before it can function properly falls somewhere between simplistic and wrong. Coser analyzed a large body of literature including Weber's writings in sociology of law, Durkheim's theory of crime and, most importantly, Simmel's essay *Conflict*. His conclusion was that social conflict must be rehabilitated as an inevitable – and necessary – part of social life.

According to Simmel and Coser, an important function of social conflict is that it binds antagonists. Unless the aim of the conflicting parties is violent mutual annihilation, conflict reinforces their awareness of social norms and often creates an intense social relationship where there used to be none. In this relationship we can usually observe repeated unintended interaction that is not part of the conflict *per se*. Thus, for example, political rivals running for an office routinely contact each other to determine a mutually convenient time for the next public debate. As they do it, the conflict between them assumes the latent function of a “socializing factor”.

One can hardly find an area of human activity where this paradoxical insight, if true, would apply more frequently and directly than in economic life. Economic competition is an obvious example of nonviolent social conflict that Simmel and Coser wrote about. Despite this, students of economy have paid little attention to the potential of competition as a “socializing factor”, and the assumption that competition alienates economic actors and hinders cooperation between them underlies most of their arguments. In my analysis, I will try to empirically

determine whether the latter approach holds its ground against the opposing idea that competition binds economic rivals and increases the likelihood of future collaboration between them.

COMPETITION AND COOPERATION BETWEEN FIRMS

“Polar Opposites”

Economic sociology emphasizes the existence and the advantages of the middle way between the competition of egoistic profit-maximizing market participants and the hierarchical integration of economic transactions. This middle way is cooperation between economic actors based on trust and personal acquaintance networks (Granovetter 1985; Powell 1990; Saxenian 1994). Unlike in vertical integration, cooperating actors retain their autonomy and identity. Unlike in competition, they tend not to contrast their own interests to those of their transaction partners.

Bringing network-based cooperation into the spotlight is a major contribution of economic sociology to the study of economic life. It has taken a firm place in the thinking of the students of economy and society (see for example Uzzi 1997; Podolny and Page 1998). Without claiming that network-based cooperation is present in all circumstances, they have developed deep skepticism towards the plain dualism of markets versus hierarchies (Perrow 1981; Robins 1987).

While the work of economic sociologists has seriously undermined the competition-or-vertical-integration dualism (however, see Williamson (1995) for an attempt to reformulate and defend it), the dualism of competition and cooperation persists in the thinking of students of economy. This dualism goes beyond regarding competition and cooperation as distinct, which

they clearly are. Rather, very much in the Parsonian spirit, authors emphasize the *oppositional relationship* between them. Their argument converges to the claim that competition between economic actors hinders cooperation between the same actors.

Browning, Beyer and Shetler do not hesitate to call competition and cooperation “polar opposites” (1995: 122). They use the example of the United States semiconductor manufacturing industry in 1980s and early 1990s to contrast those options and to argue that firms in usual conditions are highly unlikely to switch from competition to cooperation; yet they may do so when perception of a common threat – in this case, competition from Japanese manufacturers – leads to the development of a “moral community”. Trice and Beyer argue in a similar vein. They write that the “competitive ethos [of United States firms] makes cooperation across sectors or organizational boundaries very difficult. Until recently, only great national crises such as world wars have suppressed these competitive tendencies” (1993: 352).

While Browning et al. and Trice and Beyer maintain that competition forces in firms generally have the upper hand over cooperation forces, there are authors arguing that in certain business cultures they dominate in turns. These more sophisticated arguments, however, still picture a clash between competitive and cooperative forces. Thus, Saxenian, who is credited for describing conditions in which the competitive and the cooperative ethos coexist, claims that competition and cooperation are opposing tendencies even in a generally open and cooperative business culture. She reports that “cooperation [among Silicon Valley venture capital firms and among the companies they funded] was always tempered by the reality of intense competition” (Saxenian 1994: 40). Brandenburger and Nalebuff likewise do not make a departure from contrasting competition and cooperation, even though their term “co-opetition” seems to suggest the opposite. In what is rather a practical guide to business people than a scientific study, they describe advantages of a strategy where economic actors cooperate in “creating a pie and

[compete] when it comes to dividing it up” (1996: 4). Economic actors literally following Brandenburger and Nalebuff’s strategy are profit maximizers keenly aware of the fact that cooperation may impair their chances to grab the biggest possible slice of a “pie” (i.e. of the market for a new type of product). Whenever they conclude that this is the case, they opt out of a cooperation relationship. Making smart decisions about switching back to competition is a way to outperform others, so competitive considerations never stop interfering with cooperation for these actors.

Benefit Expectations and Cooperation

Authors who argue that in usual conditions cooperation is unlikely or hindered by competition are certainly aware of the fact that cooperation between firms does occur. Some of them, as we just saw, theorize cooperation as a phenomenon that recurs in times of industrial crises or when economic actors strike a truce to “create a pie”. Other researchers perform statistical analyses of behavior of concrete firms to come up with different explanations of cooperation.

Thus, Podolny (2001) argues that by creating alliances and analyzing alliance patterns firms can obtain information that enables them to reduce risks coming from different types of market uncertainty. He finds support to his hypotheses in data on venture capital. Saxton (1997) likewise claims that firms in alliances obtain knowledge that they use to optimize their performance.

In his analysis of 166 firms in new materials, industrial automation and automotive products sectors, Gulati (1995a) found that firms are more likely to form alliances if they are strategically interdependent. Gulati reasons that firms should be considered interdependent if

they belong to different organizational niches (as defined by Hannan and Freeman (1977)) and therefore possess complementary resources. Gulati and Gargiulo (1999) restate these results.

Stuart (1998) studied 150 semiconductor firms in the period between 1986 and 1992. He found that firms with high prestige, those in crowded positions and with high degree of “technological overlap” form alliances at higher rates. To explain the latter two effects, Stuart argues that firms working in the same technological areas tend to cooperate because it is in their best interest to avoid effort duplication and because “organizations are better able to evaluate and internalize the know-how of technologically similar firms” (1998: 672). His measures of crowding and technological overlap are based on the degree to which organizations’ patent portfolios cited the same antecedent patents.²

All explanations of economic cooperation considered so far postulate that firms expect concrete benefits from each instance of cooperation. These benefits attract them into alliances, and if they disappeared, firms would immediately return to competition.

Familiarity, Competition, and Cooperation

Yet are benefit expectations the only possible mechanism leading to interfirm cooperation? A substantial literature, usually associated with the term “embeddedness”, answers this question negatively. It argues that economic action does not involve cost and benefit calculation at every step. Rather, actors tend to cooperate with partners whom they trust and interacting with whom they enjoy, often at the cost of immediate economic benefit (Granovetter

² Interestingly, Stuart’s results contradict Gulati (1995a). Clearly, firms using similar technologies belong to the same rather than to different organizational niches. According to Gulati, such firms should be considered less interdependent and hence less prone to cooperate. Stuart (1998) is obviously unaware of this contradiction.

1985; Uzzi 1997). Shapiro, Sheppard and Cheraskin (1992) and Gulati (1995b) demonstrate that this type of embedded relationship is crucially dependent on actors' familiarity with each other: "through ongoing interaction, firms learn about each other and develop trust around norms of equity, or "knowledge-based trust"" (Gulati 1995b: 92).

The embeddedness argument maintains that personal knowledge leads to cooperation through the emergence of personal sympathy and trust, and personal knowledge needed to establish cooperation is created in repeated interaction.³ But here another largely ignored question arises: in what settings is repeated interaction leading to personal knowledge likely to occur?

I posit that competition is a crucial setting in which such interaction and accumulation of personal knowledge occurs. The reasons for this are many. Firstly, a pair of competitors is more likely to participate in the same professional associations than a pair of non-competitors or of randomly selected actors. Secondly, to the extent that competition in a sector is geographically localized, two randomly selected competitors will be closer to each other in space than two randomly picked non-competitors. Both of these factors increase the likelihood of a personal encounter, unless actors consciously avoid each other. Thirdly, competitors are more likely than non-competitors to learn about each other. This may be purely unintentional learning due to the effect noticed by Simmel (1950: 317) that one inevitably learns more about one's interaction partners than they deliberately reveal. Or, of course, it can be intentional learning. Some cynical observers would probably label most of the latter type of learning as industrial espionage. Yet anecdotal and ethnographic evidence suggests that indiscriminate labeling in such situations is unwarranted. While some cases are easily categorized as industrial espionage, other cases of

³ However, see Macy and Skvoretz (1998) and McKnight, Cummings and Chervany (1998) for specific conditions in which cooperation can emerge without prior history of interaction between actors.

learning about one's competitors defy offhand categorizing. For instance, in a rare first-hand account of venture capitalists' daily business routine, Stross (2001) offers an engaging description of early-days competition between Amazon and eBay and between the venture capital firms that funded these companies. Indeed, the competing teams were eager to learn about each other's strengths and weaknesses and cheered at each other's failures, but they never used the obtained information in illegal or unethical ways and also developed respect towards their rivals. Furthermore, Saxenian (1994) cites many examples when competitors *voluntarily* shared internal information.

Based on these considerations and relying on Coser's and Simmel's analysis of social conflict, I question the view of competition and cooperation as opposing tendencies, let alone "polar opposites". I argue that in certain conditions they are positively related, as competition breeds familiarity and familiarity fosters cooperation. Clearly, familiarity takes time to develop, so the effect should lag in time behind the cause. Thus, I hypothesize that *the more intense the competition between two firms in a given period of time, the more likely they are to cooperate in the next period.*

I expect this regularity to be especially salient in industries where cooperation between firms is a common practice, especially in those related to production of cutting-edge knowledge and technology. I suspect that in settings where cooperation is the exception, mechanisms leading to cooperation are more idiosyncratic, and the hypothesized effect is mitigated.

High Technology and Venture Capital

When Stuart (1998) finds that firms with high degree of "technological overlap" are more likely to form alliances, he seemingly comes close to the result that I expect to find in this

inquiry.⁴ Indeed, aren't firms in similar technological niches the closest competitors? However, Stuart's analysis does not offer a test of my hypothesis.

Firstly, Stuart does not distinguish between recurrent and first-time alliances, so the outcome that he studies includes cases of cooperation that followed competition *and* cases of repeated cooperation between long-term partners. Obviously, the dynamics leading to cooperation are different in these two types of cases, and controlling for the number of previous alliances in the dyad still does not tell which of the types dominates in producing the effect.

Secondly, it is impossible to decouple the variation in competition from technological variation in Stuart's analysis. The semiconductor industry that Stuart examined is research-intensive and technically sophisticated. All the joint projects that Stuart describes in more detail require deep expertise in a narrow field, so the circle of potential cooperation partners is all but predetermined: the partners must have expertise in some aspect of that narrow field. Which of the few possible alliances between potential partners working in the same narrow field will be realized may depend on the intensity of competition, but it strains credulity to suppose that minor differences between firms in patent co-citations are adequate measures of differences in the intensity of competition.

So, a test of my hypothesis requires data from a setting in which personal knowledge that develops in competition is minimally confounded with similarities in technological expertise. On the other hand, this must be a setting where competition and cooperation are both common.

The venture capital (VC) industry comes very close to meeting these requirements. Intense competition between some firms and collaboration on investment projects between other firms is what we routinely see in venture capital business (Banatao and Fong 2000; Kenney and Florida 2000; Gompers and Lerner 2002). Also, there are virtually no technological constraints

⁴ To be sure, this result is not central to Stuart's argument and is not expected in his hypotheses.

for venture capitalists that would force them into collaboration with certain firms and prevent them from collaboration with other firms. VC firms typically do not limit their investments to specific industries; on the contrary, they try to diversify their investments. For example, firms that invested only in one industry accounted for barely one sixth of the world's total venture investment in 2002.⁵

Beside this, there is considerable year-to-year volatility in firms' decisions regarding what industries to invest in. As can be seen in figure 1, about a third of firms' investments went to different industries than in the previous year throughout the 1980s and 1990s, and by 2002 this figure had risen close to a half (see Appendix A for the exact way the plotted measure was computed). The numbers remain roughly the same if they are recalculated for two and three year periods. This suggests once again that similarity of technological expertise determines VC firms' investment and cooperation decisions to a far lesser extent than it does for high technology firms.

[Figure 1 about here]

DATA

I developed a dataset of venture capital investments using the Securities Data Corporation's SDC Platinum database. The SDC Platinum database purports to record all VC investments in United States private companies (Sorenson and Stuart 2001: 1563) and also has extensive data on venture investment in non-US companies. As of September 2003, the database contained 197,530 investment records where the investor could be identified; 175,642 of these

⁵ Securities Data Corporation's SDC Platinum database; industries are classified into Venture Economics six major industry groups.

records can be classified as venture investments.⁶ While the earliest records in the database date from the 1940s, the results that I report are based on 122,540 venture investment records from the period from 1990 through 2002. The data from this period are the most comprehensive and reliable.⁷

With the data from 1990 and later, I constructed a dataset of 42,578 dyad-years, which has a separate record for every pair of private independent VC firms that cooperated at least once during a given year. I consider every fact of co-investment in the same company in the same investment round as an instance of cooperation.

To analyze conditions in which interfirm cooperation occurs, one also needs to consider the instances when no cooperation occurred. Following the logic of Sorenson and Stuart (2001: 1561-1562), I added a sample of 49,053 randomly selected non-occurring dyad-years to the actually occurred dyad-years. This matched sample makes up approximately 0.2% of the potential unrealized dyads. The alternative to creating a matched sample would be analyzing all of the nearly 25 million non-occurring dyad-years. While this would make it possible to design a better-fitting statistical model, performing complex variable construction (see next section) for a sample of this size is not possible in a reasonable amount of time, given the capacity of standard contemporary computer technology. So, if researchers use matched samples, they have to put up with a worse fit of the model but, importantly, not with biased estimates. Due to the work of King and Zeng (1999a,b), there is the `relogit` Stata procedure available that corrects for the bias introduced by undersampling on the dependent variable. I will discuss `relogit` in the method section in more detail.

⁶ SDC Platinum records on buyouts, acquisitions, and public market transactions are not regarded as venture investments.

⁷ Where necessary, e.g. in computing VC firms' experience, I use available data from all years.

MEASURES

Dependent Variable: A Measure of Interfirm Cooperation

The dependent variable in my analysis is the binary indicator of whether the dyad-year is realized. It is coded as 1 if there was at least one instance of cooperation between two members of the dyad in a given year and as zero for the randomly selected dyad-years with no cooperation. I abandoned the idea of designing a continuous measure of cooperation because bias correction techniques for models with continuous dependent variables do not exist.

Independent Variables: Measures of Competition during Previous Year

In this analysis, two firms are regarded as competitors to the extent that they share the same client base, given that they have not cooperated for at least three full consecutive calendar years. The client base of VC firms is comprised of their potential investment targets.⁸

The extent to which organizations depend on the same resources, especially on the same clients, is routinely used as a measure of competition in organizational ecology (Hannan and Freeman 1977). Most researchers in this tradition see firms engaged in similar economic activity

⁸ My emphasis on competition for customers does not mean that I believe this is the only important area of interfirm competition. Firms compete for other resources as well, such as labor and favorable public opinion. Don Steiny has pointed out to me that venture capitalists also compete in raising capital from institutional investors (e.g. insurance companies and pension funds). Although the theoretical argument above is obviously broader, the task of the empirical analysis is limited to testing the effect of competition for customers on the probability of future cooperation.

as depending on similar client resources (see e.g. Baum and Singh 1996; Podolny, Stuart and Hannan 1996). In addition to that, the similarity in the geographic scope of providers' activity is used as a measure of client base overlap in cases where geographic distance between service providers and potential customers affects the likelihood of transaction between them (see Sohn 2002). Sorenson and Stuart (2001) demonstrate that VC industry is such a case: VC firms tend to invest locally, and investment in a distant target is unlikely in the absence of cooperation history with VC firms in the target's region.

Relying on these leads, I construct three measures of interfirm competition: one to gauge the similarity in the geographic focus of their investments and two to reflect the similarity of their economic activity, or niche position. These measures are designed to assign high competition values to firm dyads whose members, simply put, do similar things at the same time close to each other and do not cooperate.

Similarity of geographic focus. – The longitude and the latitude of the center point of the zip code is the most detailed available measure of geographic location for the United States enterprises in the dataset. These coordinates were assigned to all US target companies. The zip codes of target companies are recorded in the SDC Platinum database, and the corresponding longitudes and latitudes were obtained from the Geographic Information Systems databases of Branner Library at Stanford University and the Heavens Above online database.

For non-US companies (receiving about 17% of venture investment between 1990 and 2002 according to SDC Platinum) I lacked data to assign geographic coordinates using zip codes. To deal with this problem, I identified the twenty biggest venture investment recipient countries besides the US, together accounting for over 95% of non-US venture investment between 1990 and 2002. I found one typical longitude and latitude for each of those countries except Canada

and assigned it to all target companies in this country. For Canada, geographic coordinates of twelve leading venture capital recipient cities were assigned to companies located in them.

The distance in miles between two companies with different coordinates, a and b , is then computed according to Sorenson and Audia (2000) as

$$d_{ab} = 3,437 \{ \arccos[\sin(\text{lat}_a) \sin(\text{lat}_b) + \cos(\text{lat}_a) \cos(\text{lat}_b) \cos(|\text{long}_a - \text{long}_b|)] \},$$

where latitude (lat) and longitude (long) are measured in radians and 3,437 is the constant that converts the result into miles. The distance between two companies with the same coordinates is fixed at 5 miles.

At the next step, I computed the average distance between the first and the second partner's target companies in the previous year weighted by investment amounts as

$$\alpha_{pqj} = \frac{\sum_a \sum_b d_{ab(j-1)} \frac{C_{a(j-1)} C_{b(j-1)}}{C_{p(j-1)} C_{q(j-1)}}}{\text{count}(a_{(j-1)}) \times \text{count}(b_{(j-1)})},$$

where j indexes the current year, a indexes target companies of VC firm p , b indexes target companies of VC firm q , C is the investment amount, and d is the distance between companies calculated as explained above. Weighting by investment amounts is necessary to assign different importance to target companies according to the proportion of the focal VC firm's total yearly investment that was invested in each specific company.

Finally, a measure of the similarity of the geographic focus of two firms in the dyad-year (the inverse of the average distance between targets) was computed as $1/\ln(\alpha_{pqj} + 1)$. In logging

the distance measure, I followed the recommendation of Sorenson and Stuart (2001: 1564-1565). They show that using logged distance one can more accurately replicate the functional form of the relationship between distance and tie probability in VC industry than using the simple distance in miles.

[Table 1 about here]

Similarity of industry focus. – The measure of similarity of industry focus stems from the idea that VC firms investing in the same industry have a similar niche position and hence compete more intensely than firms investing in different industries. The Venture Economics classification distinguishes six major industry groups: biotechnology, communications and media, computers, medical/life science, semiconductors/other electronics, and non-high technology. Adopting this classification, I calculate the measure of similarity of industry focus in the previous year as the share of total yearly investment that the two dyad members invested in the same industry in that year:

$$\beta_{pqj} = \sum_k \min\left(\frac{C_{p(j-1)k}}{C_{p(j-1)}}, \frac{C_{q(j-1)k}}{C_{q(j-1)}}\right),$$

where j again indexes the year, k indexes the industry group, p and q index the members of the dyad, and C is the investment amount.

Similarity of investment stage focus. – Early stage and later stage investments constitute separate segments of the VC market (Gompers and Lerner 2000; Podolny 2001). SDC Platinum distinguishes five stages of venture investment: startup/seed, early, expansion, later, and other. Unlike the nominal classification of industry groups, this scale is ordinal. Since we cannot assume the intervals of this scale to be equal, I collapse it to three crude categories: “early” (includes the two first categories), “later” (includes the next two), and “other”. Assuming now that the three collapsed categories are equally distinct from each other, I compute the measure of similarity of investment stage focus as the share of total yearly investment that the two dyad members invested in the same investment stage in the previous year:

$$\gamma_{pqj} = \sum_s \min\left(\frac{C_{p(j-1)s}}{C_{p(j-1)}}, \frac{C_{q(j-1)s}}{C_{q(j-1)}}\right),$$

where the notations are the same as in the previous equation, except for the s now indexing the investment stage.

Standardized competition index. – The standardized competition index combines the three competition variables just described into a single scale of competition. The index is computed as the sum of z-scores of the three variables. Cronbach’s alpha (a reliability measure) for this scale equals 0.58. Although this falls short of the widely used threshold of 0.7 suggested by Nunnally (1978), I will include the index in a statistical model as an additional check of the robustness of the findings.

Control Variables

Dyad resources. – The dynamics of cooperation and competition depend on resources the firms command. I use three measures to control for the combined resources of the two dyad members:

- 1) The combined experience of the dyad members, measured as the log of the combined number of venture investments they ever made before the beginning of the current year;
- 2) The combined network centrality of the dyad members, measured as the sum of their normalized betweenness centrality scores in the current year's VC co-investment networks;⁹
- 3) The combined yearly investment of the dyad members, measured as the log of the combined capital (in thousands of US dollars) they invested during the current year.

Resource inequality in dyad. – McKnight, Cummings and Chervany point out the importance of what they call “institution-based trust”. This is a kind of trust that develops between actors who are tied to each other loosely or not at all but believe that “the necessary impersonal structures are in place to enable one to act in anticipation of a successful future endeavor” (1998: 478). Kuipers (1999) shows that this kind of trust is more likely to develop between two people on different hierarchical levels. Organizational research, however, tends to report the opposite finding. For example, Chung, Singh and Lee (2000) find that alliance between two investment banks is more likely if their status is similar. So, similarity of resources (in this setting – similarity of status) signals what McKnight et al. call “structural assurance” to unfamiliar actors and in this way promotes institution-based trust between them.

⁹ The normalized betweenness centrality scores were calculated using UCINET for Windows (Borgatti, Everett and Freeman 2002).

Whatever the direction of the effect of resource inequality on institution-based trust and cooperation among venture capitalists, controlling for such inequality is essential. I will use the logs of the differences in centrality, experience, and investment capital (normalized by sums of these resources) as measures of resource inequality in the dyad.

Distance between dyad members. – Since VC firms tend to invest locally, the similarity of their geographic focus is confounded with how close they are located. To make sure that the effect of their geographic focus is not contaminated by that of their geographic proximity, the log of the geographic distance (in miles) between the dyad members is included in the models as a control variable.

Time both dyad members existed. – To account for the possibility that competition, familiarity and cooperation between VC firms vary with the time that both partners have been around, I control for the number of full calendar years that *both* dyad members have existed prior to the current dyad-year. The dyad-years in which either of the partners is investing before its founding year (as recorded in SDC Platinum) are excluded from the analysis. Such cases constitute roughly 3 per cent and most probably indicate that the firm was renamed, acquired, or merged.

METHOD

I use the rare event logit (relogit) procedure (King and Zeng 1999a,b) in Stata to model the effects of the right-hand-side variables on the occurrence of interfirm cooperation.¹⁰ Relogit is a modification of logistic regression for binary dependent variables whose distribution is different from that in the population but whose true distribution is known. This is exactly the

¹⁰ The Stata *.ado* file for relogit can be downloaded from gking.harvard.edu/stats.shtml.

case in my data: non-occurring cooperation ties are undersampled but we know their true number.

Relogit has a number of features that make it different from ordinary logit. Firstly, unlike ordinary logit, relogit is an unbiased estimator for this type of data. It offers the user the choice between two bias correction techniques: prior correction and weight correction. I chose the latter because it renders more robust estimates. Secondly, although the likelihood is computed as one of the steps in calculating relogit estimators, it is not a likelihood technique. There is no value in relogit that corresponds to the maximum of the likelihood (King 2004). Thirdly, relogit always calculates robust standard errors. Robust standard errors, unlike the usual ones, are calculated without the assumption of independence across observations and result in more conservative estimates of coefficients' statistical significance. Absence of the independence assumption is extremely pertinent to my analysis because many firms are involved in multiple dyad-years and thus enter the analysis multiple times.

The dyads that never broke up for more than three consecutive full calendar years enter the relogit procedure just once, with the year in which they were originally formed assigned to them. If a dyad was interrupted for longer than three consecutive calendar years and then re-emerged, it enters the analysis as a separate record. Thus, each period of cooperation effectively becomes one observation. This reduces the impact of redundant similar entries and also makes sure that the dependent variable accurately captures the switches from competition to cooperation instead of pooling together the switches and the cases of continuing cooperation, as in Stuart (1998).

RESULTS

The results of rare event logit regression of VC firms' cooperation are given in table 2. The relogit model supports my hypothesis: the more intensely the firms compete in a given year, the more likely they are to cooperate in the next year. This result is unambiguous for all three measures of competition that I use: their lagged effects on cooperation remain strong and positive when the competition variables are included in the model one by one (models 1, 2 and 3), and when two of them (model 4) as well as all of them (model 5) are entered. Since the three measures are slightly correlated with each other (all at $r \approx 0.25$), they mitigate each other's effects when included in one model.

The finding also holds for the standardized competition index (model 6). In fact, 41.3% of the dyads were initially formed after a year in which the value of the index was above the third quartile, and 62.2% followed years with the index above the median.

[Table 2 about here]

Figure 2 provides a visual illustration of my main result. In this figure, the predicted probability of cooperation is plotted against the percentiles of all three measures of competition. The solid line represents the tie probability predicted by a relogit model with just three independent competition variables. The dotted line represents the same probability calculated for model 5. As the three competition measures vary, the rest of the right-hand-side variables in model 5 are held constant at their medians.

[Figure 2 about here]

The plot shows a monotonic increase in tie probability as values of the three competition variables increase.¹¹ Although the slope of the lines does not appear steep before it approaches the ninetieth percentile, the positive relation between the competition variables and the probability of cooperation is obvious. So, a 40 percentile point increase roughly doubles the predicted probability of cooperation in the flatter part of the line based on model 5. For the model with the competition effects only, a 20 percentile point increase does the same. In this way the result of model 6 gets additional support: figure 2 graphically demonstrates that competition produces the hypothesized effect not only when its different aspects are examined separately in a statistical model, but also when these aspects are combined into a more comprehensive indicator.

To determine whether the competition variables moderate each other's effects on the dependent cooperation variable, I included the interaction terms of geographic focus similarity with industry and stage focus similarities in model 7. The interaction terms have negative effects on tie formation between VC firms, indicating that the similarity of industry or stage focus dampens the effect of similar geographic focus (Jaccard and Turrisi 2003). This, however, does not indicate that firms similar in both geographic and stage focus, or in geographic and industry focus, are less likely to cooperate a year later. Calculating the predicted probability of cooperation for model 7 clearly demonstrates that the opposite is the case. Although the moderated effects are negative, the overall effect for firms that score high on two measures is still positive. In other words, the positive additive effect of the pairs of competition variables clearly dominates over their negative nonadditive effect.

CONCLUSION

¹¹ I observed a similar monotonic or nearly monotonic increase when I plotted the actual values of each competition variable against the predicted tie probability.

My findings challenge the intuitive wisdom that competition alienates actors and hinders cooperation between them, which some researchers seem to uncritically accept. This wisdom may and may not be true if we examine competition and cooperation between two firms at one point in time, but it has clearly been falsified for cooperation in a period *following* competition. Two venture capital firms are significantly more likely to cooperate if they competed for investment targets in the previous year than if they did not. The most likely mechanism leading to this outcome is familiarity and knowledge-based trust, which are greater between competitors than between non-competitors or two randomly selected actors.

These conclusions interestingly echoed in the media in April 2004, as archrivals Sun Microsystems and Microsoft signed a ten-year cooperation agreement (see e.g. Takahashi 2004). The Microsoft CEO Steve Ballmer commented on this in the Fox News: “I’ve known [Sun’s CEO] Scott [McNealy] through thick and through thin so to speak, and we run businesses and those businesses compete, but those businesses also need to collaborate” (Fox News, April 2, 2004; transcription from the Factiva database). Of course, this alliance was born largely due to technological similarities, as it is mostly the case in high technology industry. Yet the socializing role of competition clearly features in Ballmer’s remark.

The results of my analysis are worth testing for robustness. For example, one could systematically re-test the findings for lags other than one year and with cooperation data grained more finely than into the conventional dyad-years. This may offer additional insight into the specifics of competition and cooperation between VC firms, yet it may not affect the accomplishment of this inquiry in falsifying the statement that competition between two firms hinders cooperation between them.

A separate issue left open in this paper is the generalizability of the finding. To what extent is the tendency to cooperate after a period of competition characteristic for firms outside the venture capital industry? for non-profit and non-economic organizations? for individual actors? If there is a variation in the strength of this tendency across different settings, what factors can explain it? Using survey studies and social psychological experiments to answer the last question seems to me an especially interesting line of research.

In settings where the finding holds, it naturally leads to the following concern: given that competitors are more likely to switch to cooperation than non-competitors, how can competition survive? Indeed, if those who compete tend to start cooperating after a certain period of time, then competition should eventually die out.

Of course, this is not what we observe in the venture capital industry and, I suspect, in most other settings where the finding holds. One can speculate about several possible reasons why this does not happen. Firstly, many cooperation relationships break up and actors return to competition. Secondly, new actors enter the settings and reinforce the competition. Thirdly, as more actors start cooperating in a certain sub-area, the importance of these sub-areas may decline, new “hot” ones may emerge, and the most intense competition may move into these new popular areas where cooperative relations have not yet developed. It is also worth keeping in mind that when actors cooperate in one area or project, they do not necessarily refrain from competition in other domains. These and other sources of persistence of competition are worth exploring in future research.

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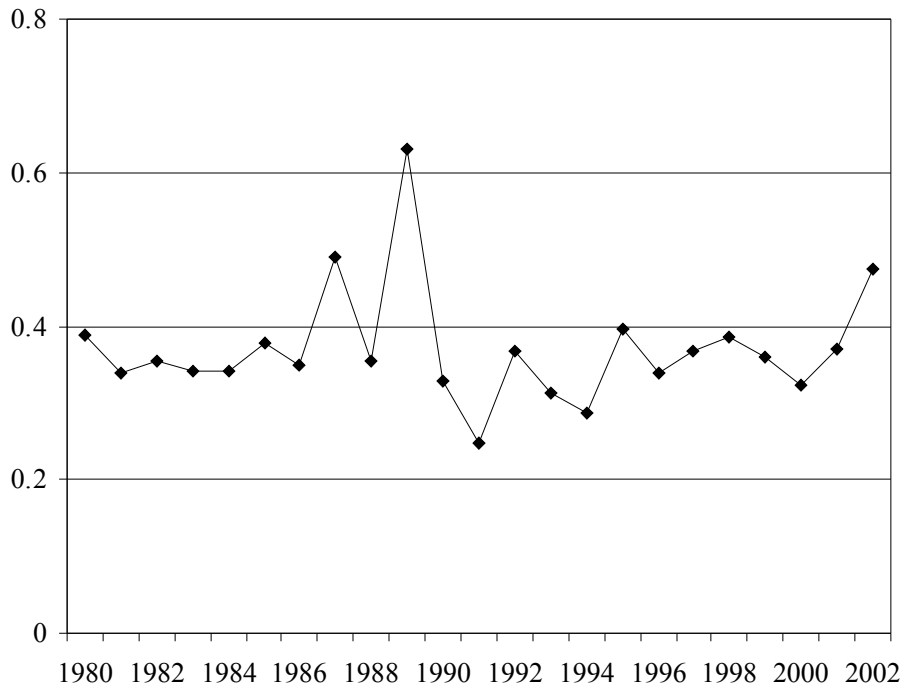


Figure 1. Venture Investment Volatility: Share of World's Total Venture Investment That Firms Invested in Different Industries Than in the Previous Year

Source: Securities Data Corporation venture investment database.

Note: Industries are classified into Venture Economics six major industry groups. For additional notes on figure 1 see appendix.



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Table 1. Descriptive Statistics of Venture Capital Dyad-Years, 1990-2002

Variable	Minimum	1st Quartile	Median	Mean	3rd Quartile	Maximum	Standard Deviation
Occurrence of co-investment	0	0	0	.42	1	1	.49
ln(combined prior experience)	1.39	3.64	4.78	4.69	5.81	8.23	1.40
Combined betweenness centrality	0	.06	.32	.69	.89	14.47	1.04
ln(combined investment (\$1000))	2.56	9.64	10.66	10.67	11.71	15.30	1.51
ln(difference in prior experience (%))	-2.54	3.62	4.22	3.92	4.49	4.60	.80
ln(difference in betweenness centrality (%))	-4.92	4.01	4.52	4.14	4.61	4.61	.82
ln(difference in investment (%))	-5.50	3.52	4.15	3.82	4.45	4.61	.92
ln(distance(miles))	0	5.70	7.38	6.47	7.92	9.21	2.28
Years both dyad members exist	0	2	4	5.60	8	53	4.96
Similarity of geographic focus	.11	.19	.26	.34	.40	7.18	.26
Similarity of industry focus	0	.13	.38	.38	.61	1	.28
Similarity of stage focus	0	.37	.61	.57	.79	1	.28
Standardized index of competition	-1.63	-.65	-.22	-.21	.23	6.03	.66

Note: N = 41,406

Table 2. Rare Event Logit Models of Venture Capital Firms' Cooperation Determinants, 1990-2002

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Intercept	-9.02*** (.19)	-9.66*** (.19)	-10.12*** (.20)	-9.60*** (.20)	-10.17*** (.21)	-9.17*** (.21)	-10.74*** (.23)
<i>Control variables</i>							
ln(combined prior experience).....	.06** (.02)	.04** (.02)	.03 (.02)	.02 (.02)	-.01 (.02)	-.01 (.02)	-.05** (.02)
Combined betweenness centrality.....	.22*** (.02)	.24*** (.02)	.24*** (.02)	.23*** (.02)	.23*** (.02)	.22*** (.02)	.22*** (.02)
ln(combined investment (\$1000)).....	.54*** (.02)	.57*** (.02)	.61*** (.02)	.56*** (.02)	.58*** (.02)	.58*** (.02)	.57*** (.02)
ln(difference in prior experience(%)).....	.01 (.03)	.02 (.03)	.02 (.03)	.04 (.03)	.05* (.03)	.06** (.03)	.07*** (.03)
ln(difference in betweenness centrality(%))	-.35*** (.02)	-.34*** (.02)	-.34*** (.02)	-.34*** (.02)	-.33*** (.02)	-.33*** (.02)	-.32*** (.02)
ln(difference in investment(%)).....	-.24*** (.02)	-.25*** (.02)	-.25*** (.02)	-.24*** (.02)	-.24*** (.02)	-.24*** (.02)	-.23*** (.02)
ln(distance(miles)).....							
.....	-.19*** (.01)	-.19*** (.01)	-.20*** (.01)	-.19*** (.01)	-.19*** (.01)	-.19*** (.01)	-.18*** (.01)
Years both dyad members exist.....	-.02*** ($<.01$)	-.01** ($<.01$)	-.01*** ($<.01$)	-.02*** ($<.01$)	-.01*** ($<.01$)	-.02*** (.01)	-.01*** ($<.01$)
<i>Competition measures</i>							
Similarity of geographic focus.....	.45*** (.17)			.32** (.16)	.27* (.16)		2.33*** (.31)
Similarity of industry focus.....		1.04*** (.06)		.95*** (.07)	.82*** (.07)		1.10*** (.12)
Similarity of stage focus.....			.94*** (.07)		.68*** (.07)		1.13*** (.13)
.....							
Similarity of geographic focus × Similarity of industry focus.....							-1.00*** (.37)
Similarity of geographic focus × Similarity of stage focus.....							-1.42*** (.38)
.....							
Standardized index of competition.....							.49***
.....							

						(.08)	
N	28993	28522	28522	28071	28071	28071	28071

Note: Robust standard errors in parentheses.

* significant at 10%; ** significant at 5%; *** significant at 1% (all two-tailed tests).

APPENDIX

A. *Measure of investment volatility.* The measure of investment volatility plotted in figure 1 is calculated as

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where i indexes the firm, j indexes the investment year, k indexes the industry, and C is the investment amount.

B. *Imputation of investment amounts.* Throughout the analysis, I use investment amounts with imputed missing values. I imputed the missing values using the regression equations where the original investment amount was predicted by 1) the average investment amount in the given investment round (the current case excluded) and 2) the average investment amount for the given VC firm in the 3-years window (1½ years before and after the given investment; the current case excluded). 8.7% of investment amounts were originally missing, as opposed to 0.7% after the imputation.

C. *Major sources of non-usable and missing cases.* The dataset that I used for multivariate modeling includes 42,578 realized venture capital dyad-years and a matched sample of 49,053 randomly selected non-occurring dyad-years. This makes a total of 91,631 cases.

Most of these cases, however, could not be used in the rare event logit models. The three major reasons for this are the following:

1. 19,781 (21.6%) dyad-years are recurring. As noted in the method section, I classify dyads as recurring if they recur before three consecutive full calendar years have elapsed. For the reasons explained in that section, recurring dyads are not usable in my analysis and are excluded from the models.
2. Previous year's investment data are missing for 30,444 (33.2%) dyad-years because SDC Platinum reports no activity for at least one of the dyad members. Values of the competition variables are undetermined for these dyad-years, and these cases are not analyzed.
3. The distance between firms cannot be computed for 6,076 (6.6%) dyad-years because the necessary information (most typically zip code) is missing.

These three sources account for over 90 per cent of all the dyad-years that could not be used in the models. Only the third one is a source of missing data. Recurring dyads are excluded for substantive reasons and, to the extent that SDC Platinum has adhered to its pledge to record every venture investment, so are the dyad-years with missing investment information for the previous year.