WHAT DO I WANT? THE EFFECTS OF INDIVIDUAL ASPIRATION AND RELATIONAL CAPABILITY ON COLLABORATION PREFERENCES

Accepted for publication at Strategic Management Journal,
Please cite original source only

Simon J.D. Schillebeeckx
Lee Kong Chian School of Business, Singapore Management University, Singapore

Sankalp Chaturvedi
Imperial College Business School, Imperial College London, London, U.K.

Gerard George*
Lee Kong Chian School of Business, Singapore Management University, Singapore

and

Zella King
Henley Business School, University of Reading, Reading, U.K.

* Correspondence to: Gerard George, Lee Kong Chian School of Business, Singapore Management University, Dean's Office, 50 Stamford Road, 178899, Singapore.
E-mail: ggeorge@smu.edu.sg

WHAT DO I WANT? THE EFFECTS OF INDIVIDUAL ASPIRATION AND RELATIONAL CAPABILITY ON COLLABORATION PREFERENCES

ABSTRACT

Research Summary

We examine individuals' collaboration preferences in the Knowledge Transfer Network (KTN) for the UK plastics electronics sector. Using conjoint analysis, we investigate how aspiration gaps and relational capability affect the value placed on potential organizational collaborations. Aspiration gaps reflect individuals' perception of whether they are ahead or behind peers on their career trajectory, and relational capability captures three distinct dimensions: networking skills, openness to collaborate, and network awareness. Our findings suggest that positive and negative aspiration gaps augment preferences to form organizational partnerships. These effects are positively moderated by networking skills and openness and negatively moderated by network awareness. We discuss the implications of these findings for theories of partnership formation, scientific collaboration, and behavioral strategy.

Managerial Summary

University-Industry collaboration is important to the creation and application of new knowledge. Such collaboration requires individuals of different backgrounds to work together, which can be difficult. We investigate what drives individuals' preferences to collaborate. We find that individuals who consider themselves ahead or behind their peers are more favorable toward collaboration. We also find that networking skill and openness augment this positive collaboration disposition whereas awareness of the network members makes one more selective and reduces the proclivity to collaborate.

KEYWORDS: aspirations, collaboration, conjoint analysis, networks, preferences, R&D

INTRODUCTION

Technological progress and the production of science are predominantly collaborative endeavors of individuals. Since specialization has become a prerequisite to advancing the knowledge frontier, collaborators increasingly bridge scientific domains and cross organizational boundaries (Jones, 2009; Wuchty, Jones, and Uzzi, 2007). Such complex collaborations have rightly assumed great strategic importance due to their prevalence and potential for value creation (Bercovitz and Feldman, 2011). Yet, collaboration across organizational and knowledge contexts is also riskier and raises coordination costs due to mutual knowledge deficits (Kotha, George, and Srikanth, 2013).

Collaboration research has acknowledged that economic relations are often "embedded in social relations of friendship and trust between people" (Kilduff and Brass, 2010, p. 324). As such, attention had been paid to dyadic characteristics of collaborations such as homophily, interpersonal trust, and affect (Casciaro and Lobo, 2008; Vissa, 2011). In addition, researchers have investigated how to access domain knowledge via high profile partners, for instance through alliances with star scientists (Hess and Rothaermel, 2011).

Within the broader literature on inter-organizational relations, there is some consensus that firm, partner, task, institutional, dyadic-relational, and network characteristics all matter (Bierly and Gallagher, 2007; Geringer, 1991; Hitt *et al.*, 2000) and that opportunities to form ties are unequally distributed (Ahuja, 2000; Mitsuhashi and Greve, 2009). Because existing ties are the outcomes of a matching process in which partners select each other (Gale and Shapley, 1962), deriving antecedents of tie formation *ex post* can only partially illuminate *ex ante* motives and preferences (Mindruta, 2013). Preferences that do not result in established ties remain hidden from investigation so that existing ties are a poor proxy for tie formation intention (Vissa, 2011). While it is not self-evident that individual preferences translate to organizational action (Powell, Lovallo, and Fox, 2011), it is also not so that what drives

people to collaborate is necessarily transparent in established collaborations (Stuart and Sorenson, 2007). Studying preferences thus allows us to look at the behavioral origins of tie formation, before the matching process comes into play.

Given the critical role played by individuals in the tie formation process, we examine how individual attributes shape preferences to form organizational partnerships. This topic has largely escaped scholarly attention, an omission rooted in the implicit assumption that individuals are homogeneous, malleable beings that are randomly distributed into organizations, thus suppressing "questions regarding motivation, preferences, [and] abilities" (Felin and Foss, 2005, p. 450). Our focus on strategy's micro-foundations, helps "to better understand the origins and the level of intentionality of aspirations in organizational practice" (Shinkle, 2012, p. 442). Survey data from KTN[1] members in the UK plastic electronics sector provide a novel context for research dominated by semiconductor and pharmaceutical studies. We use conjoint analysis (Green, Krieger, and Wind, 2001) to analyze how aspiration gaps shape collaboration propensities. While this method is commonly used in marketing and has seeped into research on venture capitalists (Franke *et al.*, 2006) and innovation (Riquelme and Rickards, 1992), our focus on variables outside the conjoint design to illuminate the role of individual characteristics, is novel.

THEORY AND HYPOTHESES

Individual Aspiration and Collaboration Preference

Decision-makers typically evaluate outcomes based on historical or social reference points, commonly referred to as aspirations (Shinkle, 2012). Facing an aspiration gap (being above or below a reference point) influences the intensity and choice of behaviors (Cyert and March, 1963). Behavioral theory argues that when people (or organizations) fall below an aspiration level they take more risks and engage in problemistic search in order to catch-up,

[1] Knowledge Transfer Networks in the UK are initiated by the government to support collaborative innovation and commercialization of new products.

while those that are ahead become either risk-averse in order to maintain their position, or use their resource excess to engage in risky, and often wasteful, slack search (Leonard-Barton, 1992; March and Shapira, 1987). Because collaboration is inherently risky (Lhuillery and Pfister, 2009), it is reasonable to assume that aspiration gaps influence collaboration preferences in a similar fashion Whether to partner with familiar or unfamiliar partners is influenced by how firms perform relative to aspirations (Greve, 2003) and underperformance drives organizations to develop new ties (Baum *et al.*, 2005). Because organizational theory "frequently discusses organizational aspirations as a managerial-level construct" (Shinkle, 2012, p. 424), this logic likely resonates at the individual level. Social Comparison Theory (SCT) suggests that negative aspiration gaps will instigate action to increase similarity so that those who are behind catch up while those who are ahead could "devote considerable time and effort to trying to improve the performance of the others in the group to a point where at least some of them are close, but not equal to, [them]" (Festinger, 1954, p. 127). Thus, while behavioral theory implies positive aspiration gaps will reduce risk-taking (March and Shapira, 1987) and hence lower collaboration preferences, SCT suggests positive gaps could lead to helping (Festinger, 1954), and thus higher collaboration preferences.

While SCT is commonly studied in the context of opinions or abilities in groups, it has not been extended to look into collaboration preferences across organizations, in which 'helping' is presumably less common. Yet, there is evidence that in emerging technological areas, cumulative knowledge development makes the entire area more valuable so that "it is in the collective interest of all participants to invest to create a substantive body of underlying scientific knowledge, and even to share this knowledge" (McGrath and Nerkar, 2004, p. 6). At the individual level, researchers have found that status benefits, having been the recipient of help before, and perceptions about those needing help are all likely to influence helping (Flynn and Lake, 2008; Grodal, Nelson, and Siino, 2015; McNeely and Meglino, 1994). It

thus seems likely that negative aspiration gaps will stimulate collaboration preferences while positive gaps result in two mechanisms pulling in different directions, so that a main effect is unlikely. If only risk averseness (helping) would matter, those experiencing a positive aspiration gap would have a lower (higher) propensity to collaborate than those who do not face an aspiration gap. Therefore, we hypothesize:

> *Hypothesis 1: Performance below a social aspiration level (doing worse than peers) will increase an individual's propensity to collaborate.*

Relational Capability as Moderator of Aspiration-Preference Relationship

Individuals are concerned with the subjective likelihood of failure when they aim to maximize expected utility (Siegel, 1957). Thus capabilities that can affect collaborative success or failure are likely to moderate the aspiration-preference relationship, because relevant capabilities can be used to influence aspirational gaps (Ansoff, 1979). In his review of the aspirations literature, (Shinkle, 2012) observed that the moderators of the aspiration-consequence relationship remain understudied.

Moving beyond previously studied one-to-one relational aspects like interpersonal trust and affect (Casciaro and Lobo, 2008), we posit that an individual's generic *one-to-many relational capability* will affect collaboration preferences. This echoes with recent findings in network research that claim that an actor's network position is likely to be endogenous, and driven by performance (Lee, 2010). For example, networks seem to be formed around high performing scientists (Zucker and Darby, 2006) and are affected by aspects of personality such as self-monitoring (Oh and Kilduff, 2008). We test whether this one-to-many relational capability, consisting of networking skills, networking openness, and network awareness, indeed affects collaboration preferences. Figure 1 provides an overview of the hypothesized relationships.

------------------------------ Insert figure 1 about here --------------------------

Networking Skills and Networking Openness

We proffer that those with better networking skills and/or more openness will exploit those traits because they enhance success probability (Siegel, 1957) and perceived behavioral control (Ajzen, 1991) (see e.g. Gulati (1999) for support at the organizational level). High openness and/or high networking skills strengthen the ambition to catch up through collaboration for those who are trailing behind. On the contrary, low networking skills and/or low openness make slackers less likely to collaborate because of reputational risks and threat rigidity (Hu, Blettner, and Bettis, 2011). Individuals who are ahead of their peers are on the one hand risk averse which would decrease collaboration preference (Kahneman and Tversky, 1979) but on the other hand want to help their distant peers come closer to them, much like a supervisor does with a PhD student (Festinger, 1954). Slack in combination with internal capabilities has been found to influence managers' likelihood of seeking alliances (Patzelt *et al.*, 2008). Merging those insights suggests that 'leaders' will be more inclined to collaborate when they perceive collaboration as safe, i.e. when they are open and/or skillful, but be averse to collaboration when they lack the needed capabilities.

Hypothesis 2a: Networking skill positively reinforces the effect of an aspiration gap on general collaboration propensity
Hypothesis 2b: Networking openness positively reinforces the effect of an aspiration gap on general collaboration propensity

Network Awareness

We conceptualize network awareness as how much an individual knows about other KTN members who are active in their focal technological domain. It thus has similarities to network centrality (Rowley, 1997) and social capital (Nahapiet and Ghoshal, 1998). While alliancing is often associated with positive outcomes (Dyer and Singh, 1998; Lavie, 2006), too many interpersonal relationships (or those that are too strong) progressively lower the mean value of created knowledge (Lavie and Drori, 2012; McFadyen and Cannella, 2004). There is thus a dark side to social capital (Gargiulo and Benassi, 1999). Specifically,

Nahapiet and Ghoshal (1998) suggest that individuals with high social capital might be less receptive to new information and diverse views. This could lower collaboration preferences.

Individual perceptions about which knowledge others have increase the likelihood of seeking out *specific* individuals for information, i.e. knowledge makes one selective in partner choice (Borgatti and Cross, 2003). Network awareness then raises an individual's ability to leverage other people's expertise (Cross and Cummings, 2004), but in doing so it heightens the opportunity costs of collaboration as well. Thus, as high network awareness might increase selectiveness, it must lower the general proclivity to collaborate, due to higher opportunity costs of working with unfamiliar people or working with familiar individuals who are known to be suboptimal for the project at hand.

These two arguments support the idea that network awareness will negatively affect collaboration outcomes. This effect will be stronger when respondents experience an aspiration gap. When individuals trail behind their peers and their network awareness is low, they will be risk-taking and positively disposed to different collaboration scenarios because they cannot be selective; however, this effect will reduce when network awareness increases. At the other end, when respondents don't face obvious resource needs because they are ahead of competition (Eisenhardt and Schoonhoven, 1996), high awareness and thus high selectivity raise opportunity costs of collaborating with the wrong partners, thereby decreasing collaboration preferences. When leaders have low network awareness they might be more prone to helping others, especially when they perceive collaboration as not too risky. While having higher awareness will make slackers more selective as well, their position of strategic need does not afford them the same selectivity as leaders. Relative to leaders, we expect them to maintain a higher collaboration preference, even when having high network awareness.

Hypothesis 2c: Network awareness negatively moderates the effect of an aspiration gap on general collaboration propensity.

METHOD AND MEASURES

We collected data from members of a UK-based KTN that supports organizations developing plastic electronics technology for displays and lighting, including SMEs, large companies, and universities. KTNs are publicly funded to improve the UK's innovation performance and offer free membership, lowering barriers to join. As within-network dynamics differ across networks due to differences in mutual knowledge (Bechky, 2003), and because specific controls required in-depth network actor knowledge, we chose to limit ourselves to one KTN within which we were able to get a decent response rate.

In October 2008, our focal KTN had approximately 800 members from 500 organizations listed in its database, including a strong representation of senior executives. An online survey was sent to all 667 members with valid email address. After two email reminders, responses were received from 201 members (30%) by the end of December. Respondents were asked to identify their seniority and role within the organization, 50 were in technology transfer or business development roles and 151 were in research-related roles. Analysis of non-response using t-tests suggested that respondents were more likely to have attended events organized by the network (69% of respondents had attended events, compared to 53% in the whole population; $p \leq 0.001$), were more likely to have prior experience of Collaborative R&D (53% of respondents compared with 40%; $p \leq 0.001$) and were more likely to work for universities than companies (32% worked for universities, compared to 22% in the population; $p \leq 0.001$).

Conjoint Analysis and Cumulative Link Models

We investigate our hypotheses using conjoint analysis. Conjoint analysis refers to the "decomposition into part-worth utilities or values of a set of individual evaluations of, or discrete choices from, a designed set of multi-attribute alternatives" (Louviere, 1988, p. 93). Conjoint analysis is often used in marketing research to study preference structures underlying buying decisions as it has great potential for measuring trade-offs between multi-

attribute products and services (Green *et al.*, 2001). The method's premise is that preferences can best be gauged by asking respondents to judge a whole product (collaboration scenario in our case) rather than by enquiring about the relative value of each product attribute (scenario variable) because asking respondents to judge how unique attributes influence preferences is not a realistic task and would ignore respondent-specific attribute complementarities. The method is especially useful and a unique approach for studying perceptions and judgments of respondents and is normally used to deduce the importance of each scenario variable (Riquelme and Rickards, 1992). However, we use the conjoint method to control for scenario variety and focus on idiosyncratic respondent characteristics that alter the average preference rating above and beyond the presented scenarios. This allows us to explore which scenario-independent variables influence differences in the response[2].

For the analysis of the data we use a cumulative link model (CLM) with flexible thresholds, also known as an ordered logit/probit model (Christensen, 2013). The core reasons for using this estimation method are: (1) it does not assume normal distribution of the response variable (collaboration preference) which otherwise biases the standard errors; (2) all predicted values will be discrete and within the permissible range (unlike GLS); and (3) the cardinal distance between the ordered ratings is not necessarily the same. This is appropriate when one does not want to assume for instance that the "mathematical" difference between "completely disagree" and "disagree" is necessarily the same as the one between "neutral" and "agree". We used the probit link which is recommended when interpreting the model with reference to a latent variable (Christensen, 2013).

We do not add fixed or random effects because in a cross-sectional dataset with multiple observations per individual, these would absorb most of the variance we aim to explain (e.g. Franke *et al.*, 2006). Even if our explanatory variables would vary within

[2] See appendix for more detail on the methodology

individuals, adding fixed effects leads to biased parameters in maximum likelihood models due to the incidental parameter problem (Lancaster, 2000). To control for unobserved heterogeneity among individuals, we calculated individual average ratings of the rated scenarios, and regressed the means of all the explanatory variables on those. The result of this regression is highly consistent with the reported regression (available upon request). We added the individual residuals from this regression as controls, as well as the mean scenario rating, excluding the rating given by the focal individual.

Response: Collaboration Preference

Respondents were asked to rate eight different collaboration scenarios. Every scenario combined one funding source, one type of organization, and four specifications about the individual partner: shared contacts, prior familiarity, shared knowledge, and seniority (see table 1). Respondents expressed low or high interest in the scenarios by rating them between 0 and 10 with mean 4.78. Our results are robust for rescaling of the dependent variable to 3 and 5 different levels. Seniority was coded as a measure of similarity using the respondent's self-reported job title. Besides funding source, which was of importance to the KTN, all scenario variables are inspection-based measures that are observable at low cost (Gavetti and Levinthal, 2000), which makes them realistically available to those seeking collaborations.

------------------------------ Insert table 1 about here --------------------------

Scenarios were rated by 3 (due to incomplete responses) up to 16 different respondents (mean 8.2)[3]. Although some scenarios were only rated a few times, this is not a problem because the explanatory power of the model depends on how many times each attribute is judged (minimally 387 times in our data). A full factorial design, in which each respondent would be presented with 192 different permutations (4x2x2x3x2x2), places excessive cognitive strain on respondents, decreases response rate, and reduces reliability of

[3] Four respondents rated more than eight scenarios as they took the survey twice. Incorporating these extra responses did not alter the results.

the results (Green, Goldberg, and Montemayor, 1981). Using a completely confounded blocks design to allow for interaction effects, all 192 possible scenarios were divided into 24 blocks of 8 scenarios so that each respondent faced as much variation in the scenario attributes as possible (Green *et al.*, 1981). Hybrid forms such as the one we used have been found to compare favorably with traditional full profile models (Riquelme and Rickards, 1992). In total, 201 respondents rated 1575[4] scenarios.

Explanatory variables and controls

Aspiration gap. We coded aspiration gap based on the following question: "Compared with people you consider peers in your chosen field, how successful has your career been? Would you say that you are ahead / level / behind your peers?" We coded this as 1 (ahead - positive gap), 2 (level - no gap), 3 (behind - negative gap). While this coding imposes equidistance between the aspiration levels, our results hold when using dummies as well[5].

Networking skills. We used the mean of six items measuring self-assessments of networking skills. The item responses range from -3 (strongly disagree) to +3 (strongly agree) Likert-type scale. Sample questions are "I very often see opportunities for collaboration between people", and "I always try to forge connections between people dealing with similar issues", etc. The factor analysis with promax rotation of these six items revealed a single factor. The reliability (Cronbach's alpha) of this scale was 0.82.

Network awareness and Networking openness. A subset of respondents that was seeking specific knowledge was presented with six names of network members with expertise in their chosen domain. Respondents were asked how well they knew the person (between 0 and 10) and whether they would want to collaborate with that person (hovering the mouse over the name displayed information about their organization). We define *network awareness*

[4] Our final sample consists of only 946 observations from 120 individuals because only individuals that were looking for specific knowledge were asked the questions that determined our moderators.

[5] We recognize that we are measuring a current gap between an individual and a social peer and that this need not equate an aspiration. Yet such gaps have been used in much of the aspiration literature (e.g. Baum *et al.*, 2005; Chen, 2008; Gaba and Bhattacharya; 2012, Greve, 2003)

as the sum of the responses to how well they knew the person. Then, we coded every response on knowledge/preference that was above (below) the respective mean as 1 (0) and summed the number of times the actor preference was above the mean while the actor knowledge was below the mean. We call this *networking openness* (between 0 and 6 theoretically, but 0 to 5 in the data). The correlation between the two variables is -0.32.

Control variables. At the individual level, we control for *job experience* (number of years in current organization) and the number of years worked before the current job. We also construct a factor that captures the *relative seniority* between the person in the scenario (junior, mid-career, or senior) and the respondent. We further include the other f*ive scenario variables*, whether the respondent's organization is *R&D active, internationally active*, and has *prior experience* with government-funded projects. Finally, we control for respondent *organization type*, the *collaboration type* the respondent's organization is interested in (marketing, operational, technological, or undefined), include (non-reported) dummies for the respondent's sought field of expertise to insulate *knowledge domain* specific effects, and *controls for unexplained scenario and individual heterogeneity*.

RESULTS

Hypothesis 1, finds support in Model 1 ($b1 = -0.93$, $b2 = 0.27$, both $p \leq 0.01$). A negative aspiration gap clearly increases an individual's propensity to collaborate, while there is also a small increase in the collaboration preference of those who are ahead. Figure 1 thus depicts a falling L-shape. All figures represent the percentage change in collaboration propensity relative to no aspiration gap at the mean of the focal variable with all significant non-focal variables set to their mean. Figures 3 - 5 show the mean and mean +/- two standard deviations. We use the coefficients from the highly similar, but non-reported full OLS model because they can be converted more sensibly to percentage changes. We perform simple

slope tests to check the statistical significance of the slopes (Robinson, Tomek, and Schumacker, 2013), and found significant t-tests for all 3 interaction effects ($p \leq 0.001$).

----------- Insert table 2 and figures 2 – 5 about here -----------

Hypothesis 2a suggested networking skills positively moderate the aspiration-gap - preference relationship. Model 2a shows significant interactions terms ($b1 = -1.08$ and $b2 = 0.28$; $p \leq 0.01$ for both). Figure 3 shows that without aspiration gap, skills do not significantly affect collaboration preference. However, when the gap is negative or positive we see those with higher skills are more likely to collaborate while those with low skills exhibit a threat-rigidity response and are less likely to collaborate (Hu *et al.*, 2011). Importantly, networking skills do not determine the aspiration gap as the means for being behind, level, or ahead of peers are 1.59/1.63/1.61, and statistically insignificant. Hypothesis 2a cannot be rejected.

Hypothesis 2b postulated a positive interaction between networking openness and aspiration gap. Model 2b supports this hypothesis ($b1 = -1.82$, $p \leq 0.01$ and $b2 = 0.34$, $p \leq 0.05$): Individuals with high openness who face an aspiration gap have higher collaboration preferences. Figure 4 shows the effects are more pronounced than for the skills moderation. The moderation effect is stronger with a negative aspiration gap: A highly open slacker is about 60 percent more favorable toward collaboration than an averagely open respondent who's level with peers. We also find negative effects for low openness.

Finally, hypothesis 2c posited that network awareness would negatively moderate the aspiration-gap - preference relationship and the results in Model 2c confirm the hypothesis ($b1 = 0.34$, $p \leq 0.001$ and $b2 = -0.09$, $p \leq 0.01$). Slackers know, on average, more people in the network with statistically significant differences in the mean ($9.66 > 8.78 > 7.61$). Figure 5 shows again the virtually zero effect of network awareness in the absence of an aspiration gap. However, when there is an aspiration gap, low network awareness makes individuals more prone to collaborate while high awareness reduces collaboration preference. Against

expectations, slackers seem to be more selective than leaders when they have high network awareness as they rate scenarios about 12% lower than leaders. Hypothesis 2c cannot be rejected. This could perhaps be due to a threat-rigidity reflex kicking in (Hu *et al.*, 2011).

DISCUSSION AND CONCLUSION

One of the predominant limitations in the strategy literature has often been our inability to understand individual preferences, which explains the relative lack of work on how individuals make choices that shape networks (Kilduff and Brass, 2010) and influence strategic action (Felin and Foss, 2005). Thus, most research on the antecedents of collaboration and collaborative invention has ignored the individual's characteristics. We theorized and found that individual aspiration gaps influence collaboration preferences and that relational capability, captured by networking skills, openness, and network awareness, moderate the aspiration-gap – collaboration preference relationship. In doing so, we overcome the problem of sample bias, inherent in most research on alliance antecedents (Mindruta, 2013) and improve understanding of the individual determinants of collaboration. Although preferences do not automatically translate to organizational action (Powell *et al.*, 2011; Vissa, 2011), understanding collaboration drivers is important to facilitate joint knowledge creation: Why and with whom researchers want to collaborate can increase the likelihood of tie formation, the knowledge-generating potential, and the success of actual collaborations, because what drives us to work together is not necessarily beneficial to performance (Saxton, 1997).

Behavioral strategists have argued that strategic decision-making matters exactly because differences between individuals perpetuate organizational heterogeneity (Bromiley, 2009; Levinthal, 2011). While scholars started looking at behavioral and psychological foundations of dynamic capabilities (Abell, Felin, and Foss, 2008; Hodgkinson and Healey, 2011; Winter, 2012), we break new ground, investigating the behavioral foundations of

collaboration. Importantly, the moderating effects of relational capability increase our understanding of the contingent relevance of individual aspirations. We found great similarity between those facing a negative or positive aspirational gap. Whether collaborations (and preferences to collaborate) are perceived to be risky depends on one's relational capability -- and this capability seems instrumental in figuring out what knowledge transfer members want to do within the network.

Given the focus on explaining individual preferences for collaboration, an important issue is to explore plausible alternative explanations. Different organizations present individuals with varying incentives for collaboration. The fact that we find differences between the responses of individuals in academia and in the private sector suggests that incentives may play a role, because one could assume that industry members face different incentives than academic scientists. A comparison of means shows that academic respondents are on average more willing to collaborate than industry respondents. This difference is most pronounced when it comes to government funding. Thus, in order to foster collaboration, funding agencies should investigate how to make government-funded projects more appealing to industry members.

Regarding aspirations, 41.48% of firm respondents argue to be ahead of their peers liken to only 21.72% of academics. This result suggests that aspirations of firm members have a stronger influence than those of their academic counterparts. Consistent with our hypotheses, we find that when splitting the sample based on aspirations, we have significant positive effects for openness and networking skills for those who claim to be ahead of or behind their peers and no effects for those who are level with their peers. The effect of network awareness is negative but not significant. Future research could investigate whether the organizational context affects the impact of individual aspirations. Longitudinal studies of individual aspirations and collaborations could also clarify to what extent engaging in

collaborations alters self-perceptions about one's career and whether higher collaboration preferences result in a higher incidence of collaborations or not.

The relative unimportance of relational capability for those who are level with peers has managerial implications. It is difficult to directly influence an individual's self-perception liken to his/her social peers, so that a manager is left with using various forms of training as levers to instigate a more positive attitude towards joint knowledge creation. Yet, our findings suggest that fostering relational capabilities is likely to be less effective without changes in aspiration levels. Future research on the behavioral origins of collaboration could investigate which other individual characteristics affect tie formation intention and explore the relations between individual preferences, actual tie formation, and successful collaborative outcomes.

In our research, we contrasted social comparison theory (Festinger, 1954) and behavioral theory (Cyert and March, 1963). We suggest that leaders in emerging technological fields are conflicted by a willingness to help others get ahead and risk-averseness. Our findings suggest that having sufficient relational capability is a necessary condition for helping to occur. The literature on help-giving has so far chiefly studied the drivers of helping, mainly looking at reciprocity (Gouldner, 1960), status implications (Flynn *et al.*, 2006), and larger cultural aspects (Miller and Bersoff, 1998), or how a helper's perception of others affect her likelihood of helping (McNeely and Meglino, 1994). More recently, Grant and Dutton (2012) found that reflecting on one's own past activities as a helper increases pro-social behavior. While most of these findings are situated in experimental settings or within organizational boundaries, our results suggest that in emerging technological fields, and under specific individual conditions of both capabilities and positive aspirational gaps, helping might transcend organizational boundaries and extend to knowledge transfer networks. This provides an exciting avenue for future research to

investigate how such boundary-spanning helping is affected by (organizational) identity and what the strategic consequences for performance or alliance success are.

Besides the importance of aspirations, some of our controls shed light on who wants to partner with whom. Significant signs for respondents being respectively more ($b = -0.27$, $p \leq 0{,}01$) or less ($b = 0.24$, $p \leq 0{,}05$) senior than a scenario partner suggest that findings on the occurrence of similarity in established ties can be driven by a reverse selection process, rather than a preference for similarity. This raises questions about whether findings on homophily are the pure consequence of an underlying preference of both partners to work similar others, or whether people in general prefer to work with someone who is at least like them or preferably 'higher up the value chain'. Additionally, despite a common belief that firms join KTNs to collaborate with universities, our findings suggest the opposite[6]. KTNs could exploit this knowledge and foster learning by specifically funding research that crosses organizational types, seniority boundaries, and previously developed relationships.

Finally, our innovative use of conjoint analysis could inspire future research. While this method is commonly used by marketers to determine desirable product attributes, we use it as a way of exposing the impact of individual characteristics on preferences, controlling for a variety of scenario attributes. This allows us, through a survey, to place people in different situations (i.e. collaboration scenarios) and investigate the characteristics that, regardless of the attributes of the collaboration scenario, influence the revealed preference. As such, this method can be used to investigate other behavioral aspects of strategic decision-making.

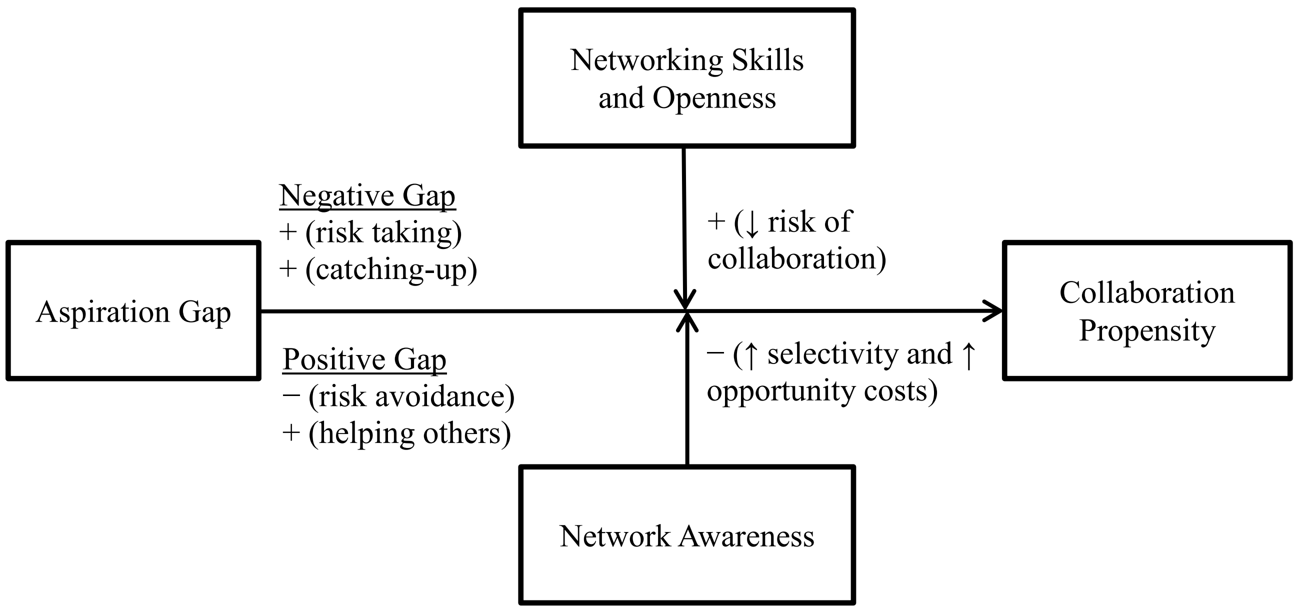
This study is plausibly among the first to show how individual aspirations can influence organizational collaboration preferences. We found the effects are contingent on complementary relational capability, which illuminates how non-focal skills play a role in the

[6] An alternative coding of the respondent organization and the scenario organization, similar to the coding for seniority, makes this very clear. One can infer the same from Model 3 as signs for both 'respondent organization is a firm' ($b = -0.21$, $p < 0.05$) and 'scenario partner organization is a university' ($b = -0.17$, $p < 0.05$) are both negative and significant.

co-creation of new knowledge. We hope future research can disentangle the differences between a star scientist, a star researcher, and a star networker as well as contingencies that determine when specific aspects of relational capability matter. Such findings will not only affect the management of R&D teams, but also and perhaps as importantly, the education of engineers and natural scientists.

TABLES AND FIGURES

Figure 1: Overview of Hypothesized Effects



Figures 2 – 5: Aspirations and Interaction Effects

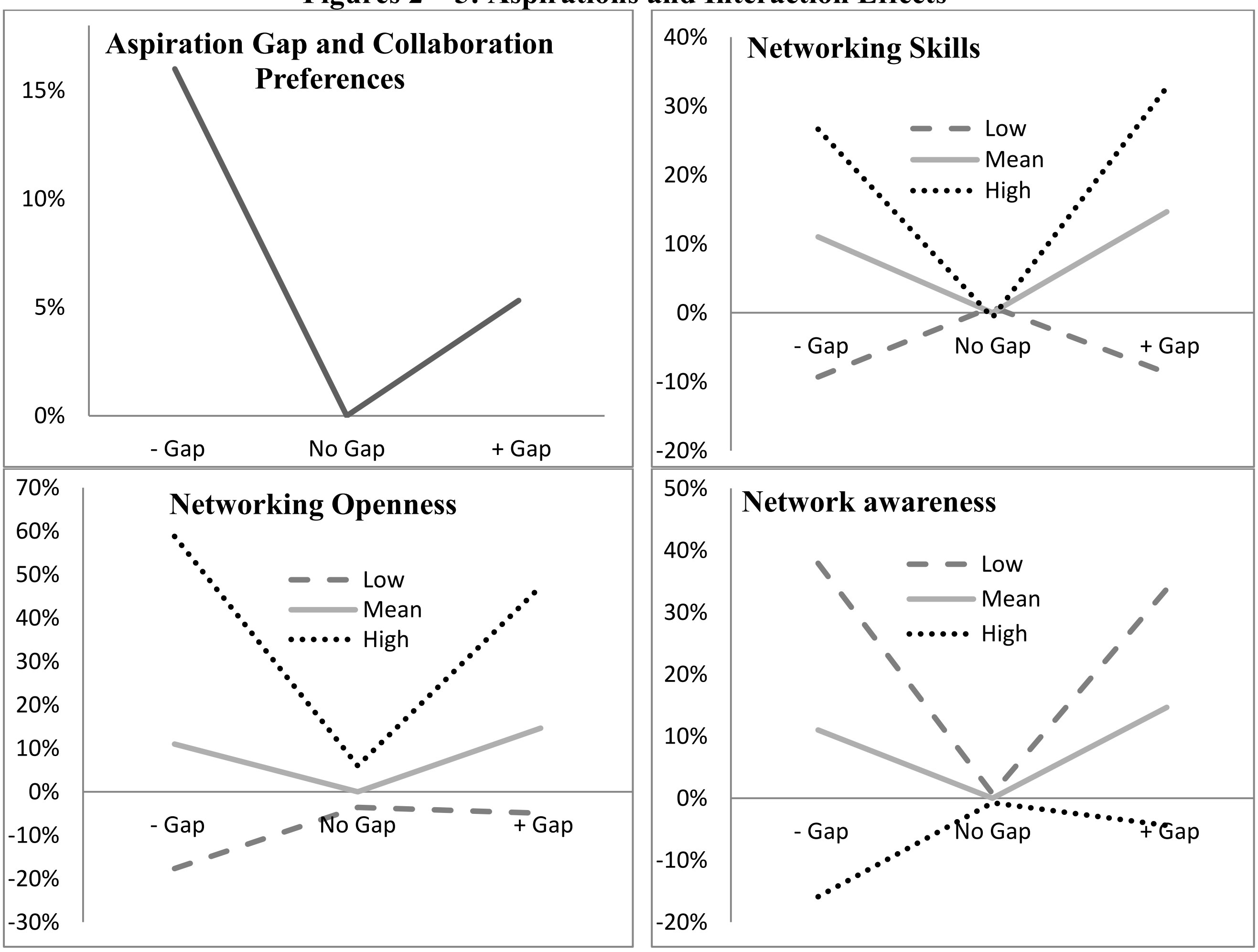


Table 1: Match characteristics and their relative prevalence in scenarios

Scenario characteristics	Level (prevalence)	Description of factor and level given to respondent
Seniority of partner	Junior (491)	Lecturer or research associate; junior scientist or engineer
	Middle (535)	Senior lecturer or reader; group leader or senior scientist
	Senior (549)	Professor; R&D or other director (e.g. CTO, CEO)
Familiarity	Distant (771)	Someone you don't know or only know distantly
	Close (804)	Someone you know well and enjoy being with
Shared Contacts	Not Known (787)	Unknown to people you collaborate/work with
	Known (788)	Known to people you collaborate/work with
Knowledge	Different (765)	Partner's work draws on different technology/science from yours
	Similar (810)	Partner's work draws on similar technology/science to yours
Resource Provisioning	No funding (387)	Informal collaboration; no funding available
	Govt. funding (389)	Government funding covers half of each party's costs
	Partner funding (410)	Partner's organization covers your costs
	Self-funding (389)	You cover the partner's costs as well as your own
Organization type	University (763)	Works for a university
	Company (812)	Works for a company

Table 2: Cumulative Probit Model: Stepwise Analysis

	Model 0	Model 1	Model 2a	Model 2b	Model 2c	Model 3
Interaction effects						
Networking Skills * Aspirations			-1.08** (0.33)			-1.03** (0.34)
Netw. Skills * Aspirations ^ 2			0.28** (0.09)			0.25** (0.09)
Networking Openness * Aspirations				-1.28** (0.47)		-0.96* (0.48)
Netw. Openness * Aspirations ^ 2				0.34* (0.15)		0.25†† (0.15)
Network Awareness * Aspirations					0.34*** (0.1)	0.29** (0.11)
Netw. Awareness * Aspirations ^ 2					-0.09** (0.03)	-0.08** (0.03)
Focal effects						
Aspirations		-0.93** (0.34)	0.81 (0.64)	0.65 (0.52)	-3.95***(0.98)	-0.66 (1.25)
Aspirations ^ 2		0.27** (0.1)	-0.19 (0.17)	-0.12 (0.15)	1.07***(0.28)	0.26 (0.35)
Networking Skills		0.14** (0.04)	1.06***(0.29)	0.13** (0.04)	0.14** (0.04)	1.07*** (0.3)
Networking Openness		0.11*** (0.03)	0.11***(0.03)	1.23***(0.34)	0.12***(0.03)	0.97** (0.35)
Network Awareness		-0.02 (0.01)	-0.02 (0.01)	-0.03* (0.01)	-0.31***(0.09)	-0.28** (0.09)
Respondent						
Experience on the job	-0.01** (0)	-0.01** (0)	-0.01** (0)	-0.01* (0)	-0.02** (0)	-0.01* (0.01)
Experience prior to job	0.0 (0)	-0.01† (0)	-0.01 (0)	-0.01† (0)	-0.01† (0)	-0.01† (0)
More senior than collaborator	-0.3*** (0.09)	-0.29** (0.09)	-0.28** (0.09)	-0.28** (0.09)	-0.29** (0.09)	-0.27** (0.09)
Less senior than collaborator	0.27** (0.1)	0.28** (0.1)	0.27** (0.1)	0.24* (0.1)	0.28** (0.1)	0.24* (0.1)
Not a researcher	-0.22* (0.11)	-0.31** (0.11)	-0.29** (0.11)	-0.32** (0.11)	-0.3** (0.11)	-0.29** (0.11)
Respondent Organization						
RandD active (1 = yes)	-0.19† (0.1)	-0.09 (0.1)	-0.11 (0.1)	-0.12 (0.1)	-0.11 (0.1)	-0.15 (0.1)
Internationally active (1 = yes)	0.24† (0.13)	0.24. (0.13)	0.27* (0.13)	0.24† (0.13)	0.24. (0.13)	0.28* (0.13)
Collaboration experience (1 = yes)	0.13 (0.09)	0.14 (0.09)	0.17† (0.09)	0.11 (0.09)	0.12 (0.09)	0.12 (0.09)
Operational collaboration	-0.11 (0.13)	-0.14 (0.13)	-0.07 (0.13)	-0.17 (0.13)	-0.12 (0.13)	-0.09 (0.13)
No Collaboration	-0.29 (0.26)	-0.13 (0.28)	-0.22 (0.28)	-0.18 (0.28)	-0.31 (0.29)	-0.45 (0.3)
Technological collaboration	0.01 (0.08)	0.01 (0.08)	0.01 (0.08)	-0.02 (0.08)	0.02 (0.08)	0.0 (0.08)
Organization is Government actor	0.01 (0.2)	0.14 (0.2)	0.19 (0.2)	0.04 (0.2)	0.19 (0.2)	0.14 (0.2)
Organization is Firm (Uni is default)	-0.25** (0.1)	-0.21* (0.1)	-0.16 (0.1)	-0.28** (0.1)	-0.19† (0.1)	-0.21* (0.1)
Scenario Variables						
Partner organization is university	-0.17* (0.07)	-0.18** (0.07)	-0.18** (0.07)	-0.17* (0.07)	-0.18** (0.07)	-0.17* (0.07)
Partner funding	0.38*** (0.1)	0.39*** (0.1)	0.38*** (0.1)	0.4*** (0.1)	0.4*** (0.1)	0.4*** (0.1)
No funding	-0.17† (0.1)	-0.17† (0.1)	-0.17† (0.1)	-0.15 (0.1)	-0.17† (0.1)	-0.17† (0.1)
Self-funding	-0.51*** (0.1)	-0.51*** (0.1)	-0.51*** (0.1)	-0.49*** (0.1)	-0.52*** (0.1)	-0.51*** (0.1)
Shared ties with potential partner	0.21** (0.07)	0.22** (0.07)	0.22** (0.07)	0.21** (0.07)	0.22** (0.07)	0.21** (0.07)
Not a close friend of respondent	-0.29***(0.07)	-0.29*** (0.07)	-0.28*** (0.07)	-0.27*** (0.07)	-0.29*** (0.07)	-0.28*** (0.07)
Similar knowledge to respondent	-0.04 (0.07)	-0.04 (0.07)	-0.04 (0.07)	-0.03 (0.07)	-0.04 (0.07)	-0.04 (0.07)
Additional Controls						
Sought Knowledge Dummies	included	included	included	included	included	included
Propensity Residual	0.48***0.03)	0.5*** (0.03)	0.5*** (0.03)	0.5*** (0.03)	0.5*** (0.03)	0.51***(0.03)
Mean rating scenario others	0.05† (0.03)	0.05* (0.03)	0.06* (0.03)	0.06* (0.03)	0.05* (0.03)	0.07** (0.03)
# Observations	946	946	946	946	946	946
Akaike Information Criterion	4,047.69	4,024.90	4,018.30	4,007.73	4,017.71	3,999.76
Log Likelihood	-1,986.85	-1,970.45***	-1,965.15**	-1,959.87***	-1,964.71**	-1,951.88**

Interpretation:, *** , $p \leq 0.001$; **, $p \leq 0.01$; *, $p \leq 0.05$; †, $p \leq 0.1$;††, $p = 0.104$ (This value was significant in the OLS model at $p = 0.064$ and is hence used in the graphical representation of the effects)
Significance of the change in Log Likelihood Ratio is determined by comparison to best available nested model

REFERENCES

Abell P, Felin T, Foss N. 2008. Building micro-foundations for the routines, capabilities, and performance links. *Managerial and Decision Economics* **29**(6): 489-502.

Ahuja G. 2000. The duality of collaboration: Inducements and opportunities in the formation of interfirm linkages. *Strategic Management Journal* **21**(3): 317-343.

Ajzen I. 1991. The theory of planned behavior. *Organizational behavior and human decision processes* **50**(2): 179-211.

Ansoff I. 1979. *Strategic Management*. Macmillan: London.

Baum JA, Rowley TJ, Shipilov AV, Chuang Y-T. 2005. Dancing with strangers: Aspiration performance and the search for underwriting syndicate partners. *Administrative Science Quarterly* **50**(4): 536-575.

Bechky BA. 2003. Sharing meaning across occupational communities: The transformation of understanding on a production floor. *Organization Science* **14**(3): 312-330.

Bercovitz J, Feldman M. 2011. The mechanisms of collaboration in inventive teams: Composition, social networks, and geography. *Research Policy* **40**(1): 81-93.

Bierly PE, Gallagher S. 2007. Explaining alliance partner selection: fit, trust and strategic expediency. *Long Range Planning* **40**(2): 134-153.

Borgatti SP, Cross R. 2003. A relational view of information seeking and learning in social networks. *Management Science* **49**(4): 432-445.

Bromiley P. 2009. *The behavioral foundations of strategic management*. John Wiley & Sons.

Casciaro T, Lobo MS. 2008. When competence is irrelevant: The role of interpersonal affect in task-related ties. *Administrative Science Quarterly* **53**(4): 655-684.

Chen W-R. 2008. Determinants of firms' backward-and forward-looking R&D search behavior. *Organization Science* **19**(4): 609-622.

Christensen RHB. 2013. Analysis of ordinal data with cumulative link models - estimation with the R-package ordinal.

Cross R, Cummings JN. 2004. Tie and Network Correlates of Individual Performance in Knowledge-Intensive Work. *Academy of Management Journal* **47**(6): 928-937.

Cyert RM, March JG. 1963. A behavioral theory of the firm. *Englewood Cliffs, NJ* **2**.

Dyer JH, Singh H. 1998. The relational view: Cooperative strategy and sources of interorganizational competitive advantage. *Academy of Management Review* **23**(4): 660-679.

Eisenhardt KM, Schoonhoven CB. 1996. Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms. *Organization Science* **7**(2): 136-150.

Felin T, Foss NJ. 2005. Strategic organization: A field in search of micro-foundations. *Strategic Organization* **3**(4): 441.

Festinger L. 1954. A theory of social comparison processes. *Human Relations* **7**(2): 117-140.

Flynn FJ, Lake VK. 2008. If you need help, just ask: underestimating compliance with direct requests for help. *Journal of personality and social psychology* **95**(1): 128.

Flynn FJ, Reagans RE, Amanatullah ET, Ames DR. 2006. Helping one's way to the top: self-monitors achieve status by helping others and knowing who helps whom. *Journal of personality and social psychology* **91**(6): 1123.

Franke N, Gruber M, Harhoff D, Henkel J. 2006. What you are is what you like—similarity biases in venture capitalists' evaluations of start-up teams. *Journal of Business venturing* **21**(6): 802-826.

Gaba V, Bhattacharya S. 2012. Aspirations, innovation, and corporate venture capital: A behavioral perspective. *Strategic Entrepreneurship Journal* **6**(2): 178-199.

Gale D, Shapley LS. 1962. College admissions and the stability of marriage. *American Mathematical Monthly* **69**(1): 9-15.

Gargiulo M, Benassi M. 1999. The dark side of social capital. In *Corporate Social Capital and Liability.* Leenders RTA, Gabbay SM (eds.), Springer.

Gavetti G, Levinthal D. 2000. Looking forward and looking backward: Cognitive and experiential search. *Administrative Science Quarterly* **45**(1): 113-137.

Geringer JM. 1991. Strategic determinants of partner selection criteria in international joint ventures. *Journal of International Business Studies* **2**(1): 41-62.

Gouldner AW. 1960. The norm of reciprocity: A preliminary statement. *American sociological review*: 161-178.

Grant A, Dutton J. 2012. Beneficiary or Benefactor Are People More Prosocial When They Reflect on Receiving or Giving? *Psychological science* **23**(9): 1033-1039.

Green PE, Goldberg SM, Montemayor M. 1981. A hybrid utility estimation model for conjoint analysis. *The Journal of Marketing* **45**(1): 33-41.

Green PE, Krieger AM, Wind Y. 2001. Thirty years of conjoint analysis: Reflections and prospects. *Interfaces* **31**(3): S56-S73.

Greve HR. 2003. A behavioral theory of R&D expenditures and innovations: Evidence from shipbuilding. *Academy of Management Journal* **46**(6): 685-702.

Grodal S, Nelson AJ, Siino RM. 2015. Help-seeking and help-giving as an organizational routine: Continual engagement in innovative work. *Academy of Management Journal* **58**(1): 136 - 168.

Gulati R. 1999. Network location and learning: The influence of network resources and firm capabilities on alliance formation. *Strategic Management Journal* **20**(5): 397-420.

Hess AM, Rothaermel FT. 2011. When are assets complementary? Star scientists, strategic alliances, and innovation in the pharmaceutical industry. *Strategic Management Journal* **32**(8): 895-909.

Hitt MA, Dacin MT, Levitas E, Arregle JL, Borza A. 2000. Partner selection in emerging and developed market contexts: Resource-based and organizational learning perspectives. *Academy of Management Journal* **43**(3): 449-467.

Hodgkinson GP, Healey MP. 2011. Psychological foundations of dynamic capabilities: reflexion and reflection in strategic management. *Strategic Management Journal* **32**(13): 1500-1516.

Hu S, Blettner D, Bettis RA. 2011. Adaptive aspirations: performance consequences of risk preferences at extremes and alternative reference groups. *Strategic Management Journal* **32**(13): 1426-1436.

Jones BF. 2009. The burden of knowledge and the "death of the Renaissance man": is innovation getting harder? *The Review of Economic Studies* **76**(1): 283-317.

Kahneman D, Tversky A. 1979. Prospect theory: an analysis of decision under risk. *Econometrica* **47**(2): 30.

Kilduff M, Brass DJ. 2010. Organizational Social Network Research: Core Ideas and Key Debates. *Academy of Management Annals* **4**(1): 317-357.

Kotha R, George G, Srikanth K. 2013. Bridging the Mutual Knowledge Gap: Coordination and the Commercialization of University Science. *Academy of Management Journal* **56**(2): 498-524.

Lancaster T. 2000. The incidental parameter problem since 1948. *Journal of Econometrics* **95**(2): 391-413.

Lavie D. 2006. The competitive advantage of interconnected firms: An extension of the resource-based view. *Academy of Management Review* **31**(3): 638-658.

Lavie D, Drori I. 2012. Collaborating for Knowledge Creation and Application: The Case of Nanotechnology Research Programs. *Organization Science* **23**(3): 704-724.

Lee JJ. 2010. Heterogeneity, brokerage, and innovative performance: Endogenous formation of collaborative inventor networks. *Organization Science* **21**(4): 804-822.

Leonard-Barton D. 1992. Core capabilities and core rigidities: A paradox in managing new product development. *Strategic Management Journal* **13**(S1): 111-125.

Levinthal DA. 2011. A behavioral approach to strategy—what's the alternative? *Strategic Management Journal* **32**(13): 1517-1523.

Lhuillery S, Pfister E. 2009. R&D cooperation and failures in innovation projects: Empirical evidence from French CIS data. *Research Policy* **38**(1): 45-57.

Louviere JJ. 1988. Conjoint Analysis Modelling of Stated Preferences: A review of theory, methods, recent developments, and external validity. *Journal of Transport Economics and Policy*(January): 93 - 119.

March JG, Shapira Z. 1987. Managerial perspectives on risk and risk taking. *Management Science* **33**(11): 1404-1418.

McFadyen MA, Cannella AA. 2004. Social capital and knowledge creation: Diminishing returns of the number and strength of exchange relationships. *Academy of Management Journal* **47**(5): 735-746.

McGrath RG, Nerkar A. 2004. Real options reasoning and a new look at the R&D investment strategies of pharmaceutical firms. *Strategic Management Journal* **25**(1): 1-21.

McNeely BL, Meglino BM. 1994. The role of dispositional and situational antecedents in prosocial organizational behavior: An examination of the intended beneficiaries of prosocial behavior. *Journal of Applied Psychology* **79**(6): 836.

Miller JG, Bersoff DM. 1998. The role of liking in perceptions of the moral responsibility to help: A cultural perspective. *Journal of Experimental Social Psychology* **34**(5): 443-469.

Mindruta D. 2013. Value creation in university - firm research collaborations: A matching approach. *Strategic Management Journal* **34**(6): 644-665.

Mitsuhashi H, Greve HR. 2009. A matching theory of alliance formation and organizational success: Complementarity and compatibility. *Academy of Management Journal* **52**(5): 975-995.

Nahapiet J, Ghoshal S. 1998. Social capital, intellectual capital, and the organizational advantage. *Academy of Management Review* **23**(2): 242-266.

Oh H, Kilduff M. 2008. The ripple effect of personality on social structure: self-monitoring origins of network brokerage. *Journal of Applied Psychology* **93**(5): 1155.

Patzelt H, Shepherd DA, Deeds D, Bradley SW. 2008. Financial slack and venture managers' decisions to seek a new alliance. *Journal of Business Venturing* **23**(4): 465-481.

Powell TC, Lovallo D, Fox CR. 2011. Behavioral strategy. *Strategic Management Journal* **32**(13): 1369-1386.

Riquelme H, Rickards T. 1992. Hybrid conjoint analysis: An estimation probe in new venture decisions. *Journal of Business Venturing* **7**(6): 505-518.

Robinson CD, Tomek S, Schumacker RE. 2013. Tests of Moderation Effects: Difference in Simple Slopes versus the Interaction Term. *Multiple Linear Regression Viewpoints* **39**(1): 16-25.

Rowley TJ. 1997. Moving beyond dyadic ties: A network theory of stakeholder influences. *Academy of Management Review* **22**(4): 887-910.

Saxton T. 1997. The effects of partner and relationship characteristics on alliance outcomes. *Academy of Management Journal* **40**(2): 443-461.

Shepherd DA. 1999. Venture capitalists' assessment of new venture survival. *Management Science* **45**(5): 621-632.

Shinkle GA. 2012. Organizational Aspirations, Reference Points, and Goals Building on the Past and Aiming for the Future. *Journal of Management* **38**(1): 415-455.

Siegel S. 1957. Level of aspiration and decision making. *Psychological review* **64**(4): 253-262.

Stuart TE, Sorenson O. 2007. Strategic networks and entrepreneurial ventures. *Strategic Entrepreneurship Journal* **1**(3-4): 211 - 227.

Vissa B. 2011. A matching theory of entrepreneurs' tie formation intentions and initiation of economic exchange. *Academy of Management Journal* **54**(1): 137-158.

Winter SG. 2012. Capabilities: Their origins and ancestry. *Journal of Management Studies* **49**(8): 1402-1406.

Wuchty S, Jones BF, Uzzi B. 2007. The increasing dominance of teams in production of knowledge. *Science* **316**(5827): 1036-1039.

Zacharakis AL, Meyer GD. 1998. A lack of insight: Do venture capitalists really understand their own decision process? *Journal of Business Venturing* **13**(1): 57-76.

Zucker LG, Darby MR. 2006. Movement of star scientists and engineers and high-tech firm entry. In *Working Paper Series.* National Bureau of Economic Research.

APPENDIX: CONJOINT STUDY DESIGN

Conjoint analysis and conjoint experiments are rather well known in marketing, but have been used scarcely in management and innovation (see Riquelme and Rickards, 1992 for an exception), though more frequently in entrepreneurship (Zacharakis and Meyer, 1998 - JBV; Shepherd, 1999 - MS; Franke *et al.*, 2006 - JBV; Fischer and Henkel, 2013 - RP). This type of research design is typically used to explore the preference structure of individuals regarding a product or service. Because individuals tend to find it difficult to rate how much they value a specific attribute of a product, the conjoint design presents respondents with more holistic and realistic options to rate. In doing so, it facilitates the process for individuals who are not required to introspectively dissect their own preference structure. As such, the conjoint method is potentially very useful to identify how individuals make trade-offs between multiple attributes of a single product or service (Green, Krieger, and Wind, 2001). As an example, think about having the rate individual attributes of a wallet (fabric, number of card slots, thickness, whether or not there is a pocket for change, how it opens, whether or not there is a transparent window for an ID card, whether there is a specific card slot for a contactless payment card on the outside…). This becomes rather complex immediately. Conjoint design presumes that people find it easier to just compare and rate various real wallets without necessarily needing to understand why they prefer one over the other.

We use this method to investigate collaboration preferences. Rather than asking consumers about a product, we presented firm and university respondents with various collaboration scenarios, determined by different combinations to six collaboration attributes. The six attributes had a total of 15 different levels between them (see table), leading to 192 different possible combinations for a full factorial design (2*2*2*2*3*4 = 192). Presenting respondents with all possible permutations places an undue burden on their cognitive capacities and would dramatically increase response time to the survey and consequentially lower response rate. Additionally such designs are argued to have lower reliability (Green, Goldberg, and Montemayor, 1981). Therefore, researchers commonly implement fractional factorial designs in which only a fraction of the total number of permutations are used or all are used but a fraction is presented to individual respondents. One such example is a confounded blocks design as we used. Such hybrid forms generally compare favourably with traditional full profile models (Riquelme and Rickards, 1992).

We split the 192 permutations in 24 blocks of 8 scenarios and each respondent rated one block of eight. In order to ensure that each scenario was rated approximately the same number of times across the whole set of respondents, the web-based survey tool allocated blocks to respondents in a sequential order, ensuring that each block is rated by about the same number of respondents. Of course, data incompleteness forced us to delete some observations so that the final data set is not perfectly balanced across scenarios. This is however not problematic as the interest is typically in finding out what the average contribution of an individual attribute to a specific scenario is.

Various computer programs can generate orthogonal designs that guarantee all (or most) combinations of attributes and their various values co-occur various times. We used a design with a high resolution (including all possible scenarios) so that interaction effects between the attributes could be estimated (Yong, 2004). Because we do not test for interaction effects specifically, researchers can use scenario fixed or random effects or control for the average rating per scenario (as we did).

Our interest in studying collaboration preferences, and our ambition to avoid the bias inherent in research that looks at established collaborations to study collaboration antecedents (Mindruta, 2014), drove us towards a conjoint method design. Although not the focus of our paper here, conjoint analysis enables us to investigate which scenario attributes are, on average, most influential in the formation of preferences. We strongly believe individual preferences are relevant in the future (attempted) formation of actual ties (Ajzen, 1991; Vissa, 2011), which makes the study of preferences important to uncover the micro-foundations of strategy (Felin and Foss, 2005). In this regard, the conjoint method provides a useful toolkit for the strategy researcher, especially those interested in micro-foundations, to study the underlying individual and firm-idiosyncratic drivers of collaborations or other organizational decisions in a granular and experimental way. Because established collaborations are the outcome of a matching process (Mindruta, 2014; Mitsuhashi and Greve, 2009), or organizational decisions regarding investments for instance are the result of compromise and/or political bargaining, conjoint analysis is a method that allows the study of the underlying root-positions of organizations and individuals. Longitudinal designs that start from preferences and ideal cases and evolve into studies of actual collaborations or investments for instance could strongly enrich our understanding of the determinants of successful performance and to what extent they are also the driving factors behind the initial decisions. In other words, the conjoint method could help uncover whether success is the result of planning or luck.