

Status as Liability for Knowledge Brokers:
A study of inter-firm relationship in a convergent field¹

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ABSTRACT

This paper investigates the knowledge antecedents of strategic alliances whose firms face convergence in their sector, i.e. photographic imaging where disparate technologies are coming together. Taking a structural viewpoint, we investigate their brokerage and status around their research and development activities manifested in their collective intellectual property right filings that we construe as a knowledge space and the structure of which is explored as a precursor for the propensity to form strategic alliances. Status emerges as a liability for firms whose location in the knowledge space render them technology brokers, especially for those which enjoy high status as defined through deference by peer firms. High status brokers exhibit a lower propensity to collaborate with peers when compared to low status but structurally embedded firms due to the competitive threats they present. The strongest alliance propensity is found among high status but structurally embedded firms. The implications of the findings are discussed

Keywords:

Strategic Alliances, Structural Holes, Brokerage, Status, Innovation, Knowledge, Technology Convergence, Imaging

INTRODUCTION

This paper asks whether firms endowed with high status are prone to prominent strategic partnerships and other forms of alliances, particularly when they play an intermediary role in the bundling of disparate patches of knowledge. Research has shown time and again that status, the prestige granted to a firm due to its position in a social structure, represent a most valuable asset. Most of the current literature assumes either explicitly or implicitly that endowment of prestige is beneficial and the literature to date bears witness to that assumption. Jensen (2008) presents a lone and aberrant study which shows that during periods of market shocks and other upheavals, the putative benefits of status do not materialize. The objective of our paper is to add to this literature by highlighting status as a liability for firms which behave as knowledge brokers in a setting with rampant convergence.

We share the structural viewpoint of Stuart (1998) in our efforts to predict alliance formation using the position of firms in their network of intellectual property rights as derived through backward citations (which we call the knowledge space). Stuart (1998) captures the technological structure of the market at the producer level through prestige (defined by deference as imputed through patent citations) and crowding (similarity in firms' innovation activity captured through structural equivalence). In contrast, we focus on technology dissimilarity as firms become detached from their traditional knowledge clusters and ask what this detachment entails for their inter-firm relationships. Detachment is presumed to occur when firms begin to draw on the knowledge of divergent peers which are typically much less technologically embedded. Our research question seeks to find an answer regarding a firm's propensity to form strategic alliances with peer firms which often confer respect and deference to firms which reside at the cross roads as one might describe brokerage

Our empirical setting is the photographic imaging sector, which has undergone convergence of chemical and digital technologies over the last three decades. Bundling disparate domains of knowledge would be an important source of competitive advantage in such rapidly changing sectors where key knowledge components face extinction through substitution or might produce rents through the recycling of existing patches of knowledge as documented by Tripsas (1997). rather than innovating in one's own niche. Therefore, brokerage is an important conceptual apparatus to capture the dissimilarities in innovation activity and predict its effect on inter-organizational relationship.

In this paper we develop theory to explain the effect of brokerage and status on inter-firm relationships. We posit that firms with more non-redundant ties will have more opportunities to form exchange relationship. We extend Stuart's (1998) argument regarding status and alliance rate by observing selection in the inter-firm relationship formation. While high status will attract partners, that endowment does not translate into organizational proclivity to forge collaborative arrangements in the sector. High status organizations may forgo joint ventures due to status leakage (Podolny, 2001) if status is unequally distributed among potential partners. Conversely, low status firms may not be willing to absorb the differential value that the high status partner seeks to extract (Stuart, 1998; Hsu, 2004).

Furthermore, we believe that the implications of firm status for strategic coordination and alignment cannot be fully understood unless one considers the network location of the firms involved. That location pertains to the connection of firms in the accumulated knowledge space that emerges from their interwoven stock of intellectual property, which can be framed in terms of brokerage and closure. Brokerage here represents a focal firm's position among all firms that mediates the bundling of technology; its opposite is closure in which case all firms are

interconnected such that no single firm stands out in integrating parts of the knowledge space. In a closed knowledge space all firms are strongly connected while in a more open or disconnected space some firms stand between other firms in tying together their stock of knowledge. If brokers enjoy high status this preeminent position threatens other firms, especially prestigious ones, particularly if the sector undergoes a major transformation or their sector witnesses a disruption in the underlying logic—for example a breakthrough innovation or a regulatory shock (e.g. Jensen, 2008). During such periods, low status firms are not prone to become actively engaged in alliance formation since they are too marginal to suspend the uncertainty that comes with technological or regulatory upheaval.

We explore these issues on data of the 35000 most important patents in photographic imaging provided with the assistance of Eastman Kodak to construct its knowledge space. Two generations of patents citing and cited by the above focal patents are collected and twenty-three Status and brokerage as derived from this evolving knowledge space are related to the level of alliance activity for 249 firms. High status brokers are found to exhibit lower levels of alliance activity compared with high status non-brokers as well as low status brokers, strongly suggesting a status liability for these firms. Thus we contribute to the status literature by exposing heterogeneity in the effect of prestige on making partners attractive, all this in stark contrast with the putative assumption that that status endowment is beneficial for all firms all firms and constitutes an attractive platform for engaging potential exchange partners (Jensen, 2008; Podolny, 2005).

In the following sections we provide a literature review of research followed by three hypotheses that are developed anchored in theories of social structure. Next, we describe our

research methods, data and analysis and conclude with a discussion of the results, limitations and future direction of research.

THEORY AND HYPOTHESES

Literature Review

Our study builds on broad streams of literature. First, the brokerage literature, more specifically those related to social networks and inter-firm relationship, second the literature on status and finally a selected body of studies on strategic alliances.

The theory and research on brokerage revolves around the debate on brokerage and closure as triggered by Burt (Burt, 1992, 2005; Coleman 1988; Ahuja 2001). Burt (1992) introduced the concept of structural holes in social networks. If firms span structural holes, they enjoy the entrepreneurial opportunity to act as “*tertius gaudens*” and reap the advantages of being unconstrained by other firms in their immediate network. A conundrum in the social capital literature has been the paradox of maintaining sustainable brokerage while suspending possible negative consequences. Brokerage provides at best a temporary advantage, which is competed away as more information diffuses in the network (Burt, 2005). Brokers might not be trustworthy particularly when not facing a closed network (Coleman, 1988). Network closure, prevails where most firms are directly or indirectly tied to each other and are likely to express high levels of trust, conformity and social control. Between brokerage and closure a persistent tension prevails. Ahuja (2001) found that closure was more important than brokerage in the global chemical industry—parenthetically a setting relatively free of high uncertainty and convergence. Burt (2005) proposed a resolution in this debate by making the case for brokers who are trustworthy. Trust is achieved through closure’s reputation mechanism, that is, actors avoid malfeasance due to the fear that it would be detected and sanctioned.

The social network literature has identified two sources of value that accrue to a firm due to its network position. First, its network position provides the firm with opportunities for brokerage (Burt, 1992, 2004, 2005; Podolny, 2005). Social networks, however, are not only "pipes" or conduits that enable access to information from others. Relationships confer status, and act as a signal of the firm's quality or of its superior standing among peers thus acting as "prisms" (Podolny, 2001).

Podolny (2005) argues that status signals quality. An investment bank or California winery commands a premium if its location in an exchange network is central. Podolny and Stuart (1995) claim that an actor's status positively affects the attention that it receives in a community of innovators as revealed by citations around technological niches.

Finally, strategic alliances have been investigated from a structural viewpoint (Shan, Kogut & Walker, 1994; Stuart, 1998). Stuart (1998) notes that a firm's prestige in its technology space has a positive effect on alliance formation. He also shows that firms that are active in technologically similar niches tend to collaborate more frequently.

Most of the current literature assumes implicitly or explicitly that status is equally valuable for all types of firms and that higher status makes for more attractive partners (see Podolny, 2005 for a thorough review). An important exception is Jensen (2008), showing that in the aftermath of profound deregulation and the elimination of legal entry barriers, high status entrants in investment banking represent a threat to incumbents which otherwise prefer partners according to their status and endowment of structural holes in their network. Our study aims to further clarify status as a liability in a knowledge space in which firms vary in their brokerage. Photographic imaging, our sector of study which evidently exhibits shocks such as rapid and

disruptive technological convergence, with attendant transformation in so-called industry logics provides us with such a setting.

Technology Convergence

The use of the term technology convergence can be traced to Rosenberg (1963) who introduced the label for documenting the history of the US machine tool industry. Convergence pertained to the emergence of a common underlying technological platform drawing from seemingly unrelated industries (Rosenberg, 1963). This notion of technological convergence re-emerged recently to describe the confluence of telecom, data communication, IT, media and entertainment into a more encompassing ICT and multimedia industry (Gambardella & Torrisi, 1998). Our treatment of convergence in contrast is closer to the technology than to product-market level because the sharpness and placement of boundaries of an industry experiencing radical technology and well epitomized in the photographic imaging sector, is extremely hard to define. Traditional framing of industry based on products and close substitutes or industry codes like the classification from NAICS do not serve the purpose as they do in otherwise stable periods (Munir, 2003; Munir & Phillips, 2002). Change involves both complement as well as substitutions, which makes defining boundaries elusive, especially as uncertainty prevails for long periods of time and institutional consolidation remains incomplete.

We define technology convergence as the evolutionary process by which disparate knowledge in previously distant industries at the outset comes together. While we do not try to characterize or empirically test convergence in this paper, it is an important contextual feature of our empirical setting. The above definition of technology convergence specifies three salient characteristics of the context of our study that are important drivers of the causal mechanisms behind our theory First, our research concerns convergence in a technology-intensive sector.

Second, at least two or more knowledge categories become more proximate. And finally, uncertainty over a long period of time is paramount.

Knowledge Space

We define knowledge space following Stuart (1998) as the knowledge structure of the market at the producer level. The firms' innovative activities are captured through their intellectual property [IPR] filings. The knowledge space is constructed through networks of IPR citations. The network comprises different knowledge domains undergoing convergence and is manifested through structural equivalence of IPR activity through citation ties. We locate firms in this space through brokerage and status and as antecedents of their propensity for alliance formation.

Knowledge Space Antecedents of Alliance Formation

Brokerage - Structural Holes in Knowledge Space

Technology convergence involves disparate knowledge domains from previously unrelated industries or technological patches coming together. Rampant convergence presents opportunities for some firms to act as brokers as such existing knowledge domains begin to overlap and consolidate. Figure 1, shows a snapshot of knowledge space where brokers span different knowledge communities representing separate domains as highlighted in the picture.

 Insert Figure 1 about here

Technology convergence is also characterized by uncertainty. Whether convergence produces complementary or substitutionary effects is unknown ex-ante. Uncertainty prevails both at the level of the product and at the level of its underlying knowledge, including creation of new knowledge. Since our focus is mainly on the supply side, i.e., that of producers, demand side

uncertainties remain beyond the scope of this study. For example, convergence can be documented in the embedding of software into the camera's lens but it can similarly be flagged when optical patents draw on photonic information processing software. We exclude the first type of convergence in this study. Podolny (2001) makes the distinction between egocentric and altercentric uncertainty - two classes of uncertainty that confront producers. The former refers to a focal actor's uncertainty regarding conversion of several inputs into outputs - for example the technology that emanates from several suppliers. For example, tennis racket manufactures acquired knowledge from material science, mechanical engineering, orthopedic medicine and ergonomic suppliers (Pennings & Kim, 20002009); digital cameras from photonics, semiconductors, display technologies to optical suppliers. The latter denotes the uncertainty faced by a focal actor's exchange partners such as competitors, clients or other upstream organizations regarding the quality of the output that the former provides to the latter - for example tennis pros choosing among various products to play with or clients of computer hardware which depend critically on the manufacturers of wafers whose (dis)continuous innovations in machine tools have profound and often unforeseeable consequences (Adner & Kapoor, 2008). Uncertainty coupled with the requirement to integrate knowledge from disparate domains induces firms' to choose hybrid forms of firm governance (Powell, 1991). Munir (2003) in his study of the photographic imaging industry attributes the prevalence of strategic alliance to such uncertainty. Firms seek non-redundant knowledge around new industry logics by seeking out partners not entrenched in legacy knowledge networks.

We expect that brokerage opportunities, as captured through structural holes, to propagate collaboration in such a sector. Structural holes in the firm's network denote the

number of non-redundant ties, with the higher the number of such ties, greater the opportunities to form exchange relationships. Hence we predict:

H1: Ceteris paribus, higher the number of structural holes in a firm's network the higher its alliance formation propensity

Status

Podolny (2005) argues that status signals quality particularly in markets where ambiguity is rampant—for example markets with intangible or novel and yet untested goods, including investment and technology markets (e.g. Arora, Gambardella and 199?). Uncertainty engenders a loose coupling between perceived and actual quality so that a knowledge supplier's status serves to reduce that uncertainty (Podolny, 1993, 1994, 2005). An investment bank or California winery commands a premium if its location in an exchange network is central. Podolny and Stuart (1995) claim that an actor's status affects the attention that it receives in a community of innovators as revealed by citations around technological niches, even if that attention is misplaced, for example when an innovation fails (e.g., Rao, Greve and Davis, 2001—Fools Gold). Citations indicate technological ties and suggest stratification depending on how central they are in their expressions of deference. For example, technological output from central, and derivatively high-status actors receives attention and might benefit from further injections compared to "lesser" technologies originating from peripheral firms. Centrality based on deference is such a status indicator and if higher, the more attractive is a firm's candidacy to other firms who seek to monetize their complementary assets, or legitimize their identity as member of the sector (Tripsas, 1997; Tripsas, 2008). Similarly Hsu (2004) shows high status venture capitalists (VC) to be the target of entrepreneurs. Entrepreneurs are willing to accept lower valuation to partner with a reputed VC (Hsu, 2004). Following their train of thought, we expect that high status firms to be more prominent as targets for alliance formation.

However alliance formation involves both search and selection. While high status of IPR producers facilitates the search of partners, it does not necessarily drive the choice and subsequent implementation of a cooperative relationship, and even more so in a setting like the earlier mentioned investment banking sector where industry logics – rules, norms and structure – are changing (Jensen, 2008). Firms are selective while choosing partners. High status actors present competitive threats to entrenched players, emerge as institutional entrepreneurs, conceivably not encumbered by tradition and established practices as they enjoy more leeway in forming new industry norms (compare Whyte, STREET CORNER SOCIETY). Thus we can expect high status and embedded firms to discriminate between partners with useful knowledge based on their status. Cooperation between high status and low status firms is unlikely due to threat of status leakage (Podolny, 2001) or because the latter is unwilling to absorb the value of status differential. Current literature (Hsu, 2004; Stuart, 1998) assumes that low status organizations are willing to absorb such premia—an assumption we question, when in periods of high uncertainty this value is difficult to gauge. Hence we hypothesize:

H2: Everything else constant, the higher a firm's status in the knowledge space, the lower will be its rate of alliance formation

Brokerage and Status

Finally we theorize about the moderating effect of status on brokerage. To do so we analytically divide the firms into four types based on whether they have high or low status and brokerage. We explore the interaction between status and brokerage from the perspective of a high status but low brokerage (i.e., embedded) firm. We do so because such high status' embedded firms are the heavily entrenched ones occupying a comparatively privileged position as incumbents which have shaped its underlying structure of the collective knowledge space.

High status brokers would be competitively more threatening to these entrenched players as they might replace them and introduce new industry logics (Jensen, 2008). We expect to isolate a stronger negative effect on alliance formation for high status brokers. For low status firms the effect will be opposite. Low brokerage organizations, i.e., firms with redundant knowledge and low status are unattractive due to status leakage. For embedded players status will continue to have a positive effect.

Therefore summarizing, we hypothesize:

H3: The interaction between status of the firm and its brokerage will be negatively related to its alliance formation rate

METHOD

Data

Photographic Imaging Sector: Knowledge Space Empirically Defined

The photographic imaging sector from 1976-2002 experienced disruptive changes with convergence of chemical and digital technologies. Imaging or photography now contains participants from multiple industries including many of its progenitors - the chemically based, silver halide photographic technologies with major players such as Kodak, Agfa, Polaroid and Fuji, for whom digital imaging technology represented a “competence destroying” discontinuity. One group of new entrants into imaging originated from the consumer electronics industry (e.g. Panasonic), and attempted to convert their experience with video cameras into digital imaging. Yet another group of firms originated from the graphic arts and printing industry and pioneered the use of electronic scanning. Finally, many entrants entered from computer hardware, software and semiconductor industries (e.g. Intel, Hewlett Packard, Adobe) as digital cameras began to be

accepted as computer peripherals. Thus, photographic imaging today draws on technological competencies from the semiconductor and electronics industries, computer hardware and software industries, and conventional film based imaging industries.

The delineation of sector boundaries is often carried out by conveniently available categories such as patent class or some industry classification based scheme like NAICS or SIC. While NAICS/SIC codes have a technological product focus, patents are strictly based on claims, not on industry, function or effect. We chose to construct a spatial unit by consulting industry experts in the imaging sector to provide a set of "focal patents" to define the pertinent space. Scientists and IPR experts at Eastman Kodak provided us a search algorithm through Micropatent, a US patent search provider, and collected a set of thirty-five thousand odd focal patents filed in the USPTO that are deemed central in the imaging sector and which is used by Eastman Kodak for conducting intellectual property intelligence. They categorized each focal patent as either having a chemical or digital legacy. We adopted a triangulated search algorithm to validate the choice of these focal patents by consulting other experts and using Derwent, another patent database. The focal patents furnished by Eastman Kodak do in fact capture the important patents in imaging. The chemical patents correspond to International Patent Classification (IPC) class G03C while digital patents are a mix of around 300 different IPC classes with H04N, G06K and G06F accounting for half the focal patents. Therefore, the map of the knowledge space that we furnish here is based on the Kodak furnished domain of intellectual property. This Kodak defined knowledge space furnishes a unique window into the evolutionary trajectory in this dynamic and converging sector.

Several authors have tried to categorize patents and the European Patent Office even provides an IP "web-guide" by country, scientific field and other classes. Hall, Jaffe and

Trajtenberg (2001) (HJT) classified US patents into six technological categories: Chemical (excluding Drugs); Computers and Communications (C&C); Drugs and Medical (D&M); Electrical and Electronics (E&E); Mechanical; and Others (Hall, Jaffe, & Trajtenberg, 2001). They correctly indicate the arbitrariness in devising such an aggregation system and in assigning the patent classes into various technological categories. However, their classification scheme is useful for creating topography of the photographic knowledge space. Two of their broad categories, Chemical and Computer & Communication (C&C) crudely capture knowledge in Chemical and Digital domains. By contrast, the Electrical & Electronics category captures only a small portion of that knowledge which is related to semiconductor patents and should not affect the overall characterization of the knowledge space. We employ novel clustering methods to capture the different technological domains, however at this stage we do not yet have a method to obtain stable clusters over time as discussed below in the limitations of our research.

Once we obtained the 35,473 focal patents we also collected two generation of patents that these focal patents cited and were cited by over the period 1976-2002 from the USPTO. We used the NBER patent dataset (Hall, Jaffe, & Trajtenberg, 2001) to obtain information on the citations and the pertinent technology categories. While the overall patenting rate has increased over the years, the relative importance of Chemical and Digital (proxied by C&C) has reversed. Chemical patents are still relevant in the knowledge space but are no longer pre-eminent. This switch occurred in the late eighties as shown in Figure 2.

 Insert Figure 2 about here

Next the inter-firm network in the knowledge space through backward patent citations was extracted. The focal patents yield a universe of 178,795 patents from 1976-2002 through

backward and forward citations that are assigned (conferred legal ownership) to 18,371 unique proprietors including firms, individuals, government agencies, universities and hospitals. We were interested only in firms as assignees, so we discarded all other ownership classes reducing them to a set of 17,400 firms. We further checked for duplicates and joint ventures by using a name-matching algorithm. We assigned to the parents of each joint venture the patents in proportion of the number of firms in the joint venture. This laborious process reduced the number of firms to 16,475 and constitutes the set firms in the imaging field - the population used to calculate the firms' knowledge space attributes. Twenty-three networks were constructed, using a sliding window of five years from 1976 employing Pajek, a tool for creating and analyzing large networks (Batagelj & Mrvar, 1998) and the *igraph* library for complex network analysis in R (Csardi & Nepusz, 2006).

Data Sources

The data from this study came from a variety of sources. The patent data are obtained from the USPTO, stored in readable format by the NBER and compiled by Hall, Jaffe and Trajtenberg (2001) as described above. For the alliance data SDC platinum was sourced. The focal population comprised of incumbents with imaging patents as defined by Kodak's thirty five thousand focal patents and its 3016 assignee firms. This focal set is our population of interest for the alliance analysis. We searched SDC platinum for data on their alliance activity. For the period 1984-2002 alliance data on 249 firms from SDC were available. Since prior data are unreliable, a ten-year window from 1989 to 1998 was selected to predict their alliance formation. The sample of 249 firms is a convenient, rather than a random, sample of firms that have at least one alliance reported in SDC. This should be kept in mind when generalizing to the entire population or to other knowledge intensive sectors. However, we think it captures most of the

firms engaging in strategic alliance in the ten-year time period and is representative to predict alliance propensity of firms. Additional sample selection issues are further discussed below.

Variables

Dependent Variable

Table 1 provides definitions of all the variables we used while Table 2 provides summary statistics and pair wise correlations. This dataset contains factors in the knowledge space for predicting alliance formation in each period of observation. The unit of analysis is the firm-year. A record was created for each firm in each year of the period covered in this study. Our dependent variable is *Alliance*, a count of the number of alliances for each firm every year, which captures the rate of alliance formation. We lag the variable *Alliance* by a year consistent with prior research (Gulati, 1999) and with our presumption regarding patent citations as leading indicators of technology convergence while alliance formation forms a lagging indicator. Alliance data are available from 1984 onwards from SDC. Previous research has reported that alliance activity was minimal before the 1980s (Gulati, 1999) and as mentioned, the data available from SDC are not very reliable before 1988. Therefore we obtain the alliance count from 1988 to 2001 and lag it by one year for our analysis.

 Insert Table 1 & 2 about here

Next we discuss the four independent variables of interest that derive from the imaging knowledge space.

Independent Variables

Constraint

To capture brokerage we calculate Burt's constraint, which captures the role of tie strength and group cohesion (Burt, 1992, 2004, 2005). Operationally, the construct can be viewed as capturing firms with varying degrees of structural holes in their network and which need to contend with the pressures that emanate from that network to the extent that peers are highly connected among themselves. The more the so-called alters are directly or indirectly linked, the greater their joint normative pressures on the focal firm. A firm's constraint would be very high if it has mutually stronger related (i.e. more redundant) ties. Constraint is the inverse of brokerage in that firms disconnected in a focal firm's network do not impinge on its discretionary actions – with, as a common consequence, the opportunity for that firm to act as an intermediary. In the present context, we ask whether a firm's citation linkages involve firms whose IPR exhibit low or high levels of connectivity with that of peers. The greater that connectivity, the more the firm is entrenched and the lower its discretion to act unilaterally. The formula for this construct is:

$$B_i = \sum_j (p_{ij} \sum_q p_{iq} p_{qj})^2, \text{ where } p \text{ represents the proportional tie strength between two nodes.}$$

Status

Following Stuart (1998) we use the indegree of the network of patent citations among firms encompassing five-year window from t to $t-4$ as a proxy of status. Status derives from deference relationships and patent citations are such exchanges of deference. Audiences in the knowledge space, that is other firms and patent examiners, confer status to a firm by dint of citing a patent as a valuable piece of prior knowledge. Bonacich's eigen vector centrality, which is commonly used to proxy status, cannot be invoked because for large networks the eigen vectors of such large and asymmetric matrices cannot be calculated.

Control Variables

We also included several additional control variables. *Community membership*, in line with the crowding variable in Stuart (1998) captures structural equivalence. We detect communities or blocks of similar knowledge in our networks of interest and define core and periphery. The standard procedure consists of block modeling (de Nooy, Mrvar, & Batagelj, 2005; Scott, 2000; Wasserman & Faust, 1994). However, conventional block modeling techniques are inefficient and therefore not feasible for large networks due to memory and computational limitations. Recent advances in network science has given us tractable alternatives for detecting communities in complex systems (Girvan & Newman, 2002; Newman & Girvan, 2004). Community structure detection is related to that of clustering. A community consists of a subset of nodes within which the ties are dense, and the ties to nodes in other communities are less dense. These techniques exploit the fact that many affiliation networks have a fractal-like structure in which vertices (agents, firms or actors) cluster together into groups that then further shows pattern of groups within groups (Clauset et al., 2004). We use the *fast-greedy* algorithm defined by Clauset et al. (2004) to detect communities in the twenty-three networks that define the evolving knowledge space.

Innovation impact, the effect of the influence of a firm's innovation is also controlled for. Following the practice in patent based literature (Hall et al., 2001; Jaffe et al., 2002a; Jaffe et al., 2002b) we measure this by calculating the forward citations received by a firm's patent. This is captured by calculating the outdegree of the network of patent citations among firms in the network encompassing the five-year window from t to $t+4$.

We proxy the technology capabilities of the firm by using a count of the patents in four of the main technology categories as defined by Hall, Jaffe & Trajtenberg (2001) in each year of the

ten year period in focus. The four variables constructed are *Chem IP* representing Chemical, *C&C IP* representing Digital, *EEE IP* representing Electrical & Electronics, and *Mech IP* representing Mechanical capabilities. Additionally we define *Total IP*, representing the count of patents of the firm in our knowledge space. This variable controls for participation in the imaging knowledge space. Finally, we include a variable, *IP Flow* to proxy for the overall number of patents granted to each firm in a given year to control for firm size.

Other firm level resource endowments are germane to the propensity of firms to engage in strategic alliances. The stock of alliance experience increases the likelihood of firms to replicate such governance forms through developing capabilities in forming such partnerships. In line with Gulati's (1999) research we create a variable, *Alliance experience* representing prior alliance experience of the firm. The variable is the cumulative total of alliances that the firm has entered until the previous year.

Research Design & Method

In the ideal experiment to test our research questions, a set of randomly chosen firm from the population of firms in the sector would receive the treatment of being assigned the independent variables of interest. The alliance activity of this group would then be compared to a control group. However, this is not possible as we have observational data on a subset of firm that undertake alliance. Therefore causality will be assumed using a response schedule defined below based on our theoretical arguments. Confounding issues, the model and method of analysis is described next.

Confounding & Inferential Issues

The major confounding in this case is that the knowledge space variables and alliance activity are interdependent event and therefore reverse causality could potentially lead us to wrong inferences. Also unobserved firm level time invariant fixed effects might potentially explain alliance formation. To offset this risk, a fixed effects model on panel data is employed together with a lag of the alliance count, that is, the knowledge space variables at time t will predict the alliance activity in time $t+1$. Furthermore, three of the four independent variables are calculated for a network of patent citations from $t-4$ to t , while the third, innovation impact is calculated for a network of citations from t to $t+4$. We believe that confounding due to reverse causality is reduced because of the use of these five-year windows. Also, given that firms have relatively little flexibility when it comes to citing other firms' R&D output compared to for example academic citation with their "commons" and "public goods" identity, and moreover often incur licensing fees not to mention the presence of a third party, i.e., a patent examiner, the confounding issues due to reverse causality is greatly attenuated. In short, we believe, it is rather counterfactual to claim that alliance activity influences independent variables as we have operationalized.

A related confounding issue involves time variant firm attributes, which are correlated with the independent variable. Our regression attempts to account for such attributes as far as possible. Sample selection that could limit the generalization of our results will be further discussed below.

Model, Method and Analysis

The research design models alliance formation over time as a Poisson process and approximates a quasi-experiment in which rival hypotheses are ruled out. However, the data

show over-dispersion with variance much larger than the mean mandating instead a negative binomial model for the regressions. We use a conditional fixed effect Negative Binomial for panel data as used in most of the patent literature for over-dispersed count data (Hausman, Hall, & Griliches, 1984). The negative binomial model is a generalized form of a Poisson model where an individual, unobserved effect is introduced in the conditional mean (Greene, 1997):

$$E(\text{Alliance}_{it+1} | X_{it}) = \exp(\beta'X_{it} + \alpha*\text{Allianceexp}_{it} + v_i + \delta_t + \mu'F_{it} + \varepsilon_{it})$$

Alliance_{it+1} is the dependent variable, the number of alliance by firm i at time $t+1$. X_{it} is a set of variables that characterizes the firms in the "knowledge space" and is based on the patent data as described above and listed in Table 1. The stock of strategic partnering (Alliance experience) of a firm at a particular time has been shown to be a predictor of alliance formation and therefore is included as control variable through the firm's cumulative alliance count till time $t-1$ (Gulati, 1999). The variable v_i is a set of firm dummies to capture firm fixed effects and δ_t represents year dummies to capture time trends. F_{it} is a set of financial variables to account for the size of the firm, profitability and resources in case they affect alliance activity. ε_{it} is everything else that influences alliance formation not captured by the technology, financial and experience variables and the firm and year dummies. We assume a one-year lag between our dependent variable and our regressors.

We use the *xtnbreg* command in STATA with the *fe* option to fit our data to the conditional fixed effect negative binomial model. Allison and Waterman (2002) point out that the conditional fixed-effects negative binomial model is not a true fixed-effects model since it fails to control for all of its predictors. Therefore to verify our results we also fit a Poisson fixed

effects model although it does not handle over-dispersion. Additionally we use Simcoe's *xtpqml* STATA code for robust standard errors in the Fixed Effects Poisson Model (Simcoe, 2007) based on Wooldridge (1999), which shows that the fixed effects Poisson estimator produces consistent estimates of the parameters in an unobserved components multiplicative panel data model under very general conditions (Wooldridge, 1999). The models we report here do not have any financial control variables as in separate explorations, we found that they don't have any effect on alliance formation as enunciated by prior literature (Gulati, 1999).

Results

Table 3 shows the results from our regression analysis. We only report the results from the conditional fixed effect negative binomial regression using *xtnbreg*. Consistent results with *xtpqml* and *xtpoisson* are obtained, which are not reported here. We report five models with each of our independent variable sequentially added and with all the control variables included. Our results and interpretations are presented next.

 Insert Table 3 about here

Interpretation and Discussion of Analysis

The first hypothesis considers brokerage and alliance propensity. *Constraint* inversely captures brokerage in that high constraint implies fewer brokerage opportunities while low constraint signals many structural holes and, derivatively, many opportunities. This variable is negative and significant at 5% for all the models it is part of. Thus higher constraint implies lower alliance rate giving credence to H1.

Status is also found to be negative and highly significant in model (3) and (4). Thus H2, which assumes status leakage and loss aversion (Thaler, 1984) to be rampant in imaging - a typical converging sector, is also supported in that high status diminishes alliance propensity.

Finally we look at the interaction effect of *Status* and *Constraint* to test H3. The interaction effect could be spurious, hence a Likelihood Ratio (LR) test between model (3) and (4) was performed. The LR χ^2 test was highly significant (p-value of 0.0025) so that the interaction is positive and significant. H5 is therefore supported. To illustrate the interaction effect we present two plots in figure 3.

 Insert Figure 3 about here

Figure 3 plots lines of equal alliance rates for different values of status and constraint. As we can see the contour plot can be divided into four quadrants corresponding to the two by two matrix in figure 7. In the top right corner we encounter a very steep slope for firms whose effect of status and constraint is strongest. These firms combine the role of entrenched incumbency with the endowment of status (or quality), which render such firms attractive as alliance partners. These are firms that are highly embedded and have high status in the knowledge space. The alliance rate for this group as illustrated by the interaction effect is highest. The climb in the contour plot is steep suggesting a very strong interaction between constraint and status. We call this group of firms the *Embedded High Status* group. These are firms with legacy in the technologies before convergence wreak havoc and they ally among themselves and other low status players because they might want to figure prominently in the sector for setting its agenda. In our data set Fujifilm, Konica, Agfa, Canon and Eastman Kodak are examples of firms that belong to this category. Within this group we also observe heterogeneity in behavior over time.

Kodak, for example, has become less embedded while Agfa & Konica have remained high constrained and high status players.

The joint effect of brokerage and status is much less pronounced for the other three quadrants; at least their multiplicative effect does not produce successive sequences of rapidly rising plateaus. *Low Status Brokers* reside in the lower left corner. These are firms with low status yet many brokerage opportunities. Dell and Adobe Systems in the later period of the research window illustrate this kind of firms. *High Status Brokers* predominate in the lower right corner with prominent prestige and numerous brokerage opportunities. Their alliance propensity is lower than that for *Embedded High Status* firms and *Low Status Brokers*. IBM, HP & Sony represent them in our sample. They clearly suffer from a liability due to their high status.

Finally, the top left corner contains *Embedded Marginals* - firms deprived of brokerage opportunities and suffering from low status, rendering them unattractive; others shun these firms in the knowledge space. Adobe Systems and Dell in 1990 are examples of this type of firm.

Among the effects of control variables, *Alliance experience* is positive and highly significant, in line with expectations. All year dummies except for 1990 are highly significant. Participation in the knowledge space is significant at 10%. Patenting in the three major categories, Chemical, Computer and Communication and Electrical and Electronics is negative and significant. This lends further credence to our hypothesis of threat and status leakage.

Caveats and Limitations

Our analysis is not free from important limitations that we plan to address in the future. First, as we pointed out earlier we rely on a non-random but representative sample of firms for

alliance propensity in the imaging space. Ideally we would like to develop a self-selection model that also predicts alliance formation and hence is more generalizable. Hilbe (2007) points out that Heckman and similar treatments of sample selectivity are not appropriate in models where the dependent variable represents a count. Recent work on endogeneity and sample selection for panel count data along with a selection model of alliance formation could lead to a sample self-selection model (Greene, 2008; Terza, 1998), yet this is in the cutting-edge of present day econometric research and presents significant challenges. Another option consists of a propensity score matching between selected firms in our sample and a comparison set of firms from the same population, but not included in the our sample (Rosenbaum & Rubin, 1983). In view of the alliance-active firms in the present investigation versus those that are not (or are to a much smaller extent), an adequate overlap between those two categories is hard to come by (see Table 4 for descriptive statistics on sample and population). Most of the firms outside the sample but in the population involve those that are passive - small private firms from both US and abroad with near insurmountable obstacles for information gathering involving other information than IPR. Hence, our results should therefore be interpreted conditional on alliance activity being observed.

Insert Table 4 about here

Second, we fit our model using a procedure considered problematic (Allison & Waterman, 2002). The use of multiple methods notwithstanding, the reliance on the conditional fixed effects negative binomial regression requires further scrutiny and perhaps we need to write our own procedure that implements the best model for our tests.

Third, our patent data have their usual limitations (Hsu & Lim, 2008), including, for example, IPR data that entail patent-examiner imposed citations and “strategic” citations by firm. However, we think that in our case this is not an important issue as discussed above.

Finally, we have restricted the corporate development space to alliances only. Firms engage in a wide range of behaviors to extend their strategic boundaries such as for example technology licensing, M&A and corporate venturing. Sectors with high levels of R&D intensity are also prominent markets for technology in which buyers and sellers meet through various governance arrangements (Arora, Gambardella,199). We have not even differentiated between the different forms of alliances, which might range from fifty-fifty joint ventures to arms length contracts and R&D partnerships; rather we have included all forms of cooperation.

DISCUSSION AND CONCLUSIONS

This paper sought to expose a connection between brokerage and status in a well-bounded knowledge space together with the subsequent strategic collaboration among the corporate owners of proprietary knowledge. We conceptualize the knowledge space as a brokerage and status arena that comprises of various technologies associated with what we have called the (pin hole based) photographic imaging sector - still and moving imaging, the firms of which are represented topographically in a knowledge space derived from a network of patent citations. In order to expose such a connection, we theorized that patent citation network of owners of intellectual property proxies' complementarities and substitution and motivate firms to strategically and organizationally bundle their knowledge in order to exploit it commercially.

The main finding of this study points to strong but non-linear relationships between the firms' topological location in their knowledge space and the rate at which they engage in joint ventures and other forms of strategic cooperation. Their location has two major features - brokerage and status, which interact in non-linear ways towards alliance propensity. The results suggest that the firms evolve into divergent strategic players, the prominent among them performing a trend-setting role in driving industry evolution and solidifying of technological standards and who discriminate between high status and low status brokers due to the competitive threats they pose. Thus brokers with high status face a liability as exchange partners during periods of convergence.

Thus far our study provides limited but useful insight both for research and practice of the evolving imaging sector. We show that high status is not always a desirable characteristic for an exchange partner to be endowed with. High status can be a millstone, especially for brokers in industries undergoing change in its underlying logic. We refined Stuart's (1998) argument about the effect of status by showing that both search and selection important to model alliance formation. Selection process of partner may reverse the effect of higher number of opportunities due to high status depending on the context.

This study opens up a variety of interesting issues for researchers in strategic and technology management and students of networking. Much of the conventional IPR research has centered on innovation, property rights and assets defining strategic options. The concept of a brokerage and status system is instructive for circumscribing the social structure within which firms compete and cooperate. Structural analysis should gain in prominence as investigators begin to uncover antecedents of strategic behavior that have eluded research on alliances—newly

emerging practices that the research to date has not traced to firm idiosyncratic qualities such as its accumulated IPR, its quality and connectedness to other firms in its environment.

Figure 1. Brokerage in Knowledge Space 1976-1980

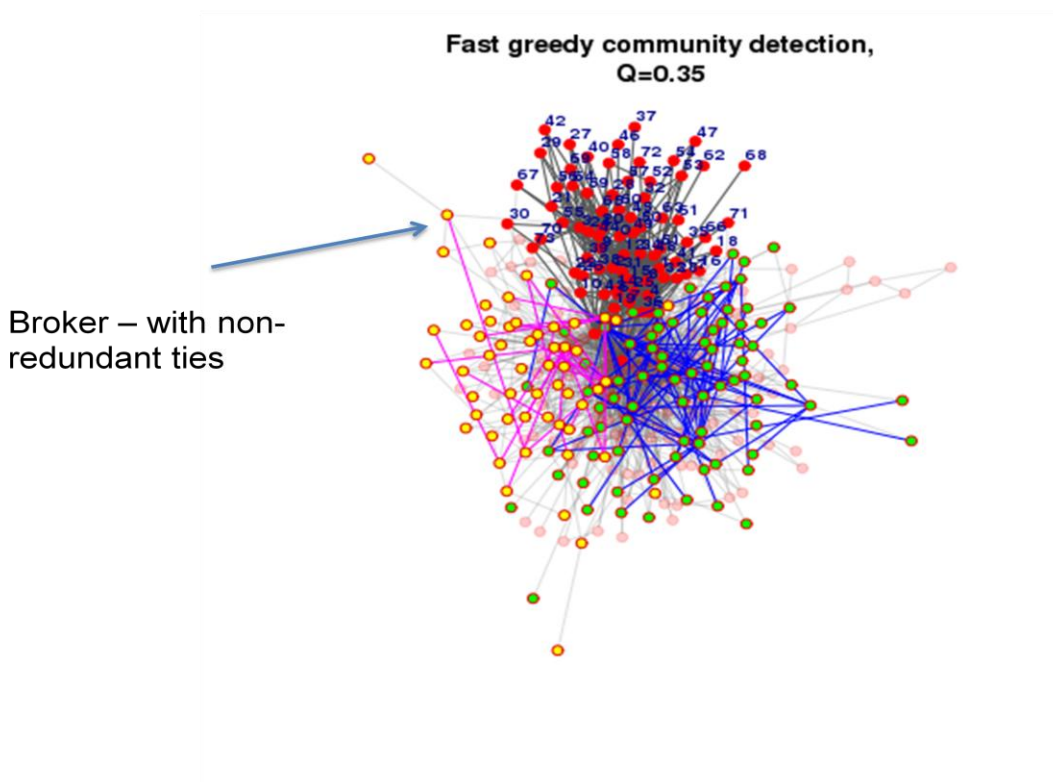


Figure 2. Chemical and Digital patent evolution from 1976-2002

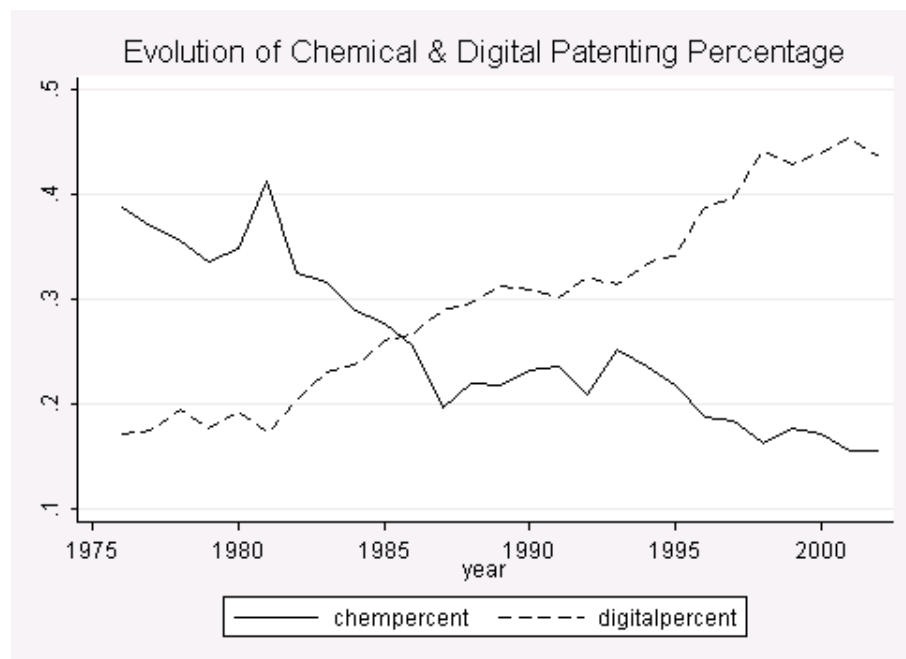
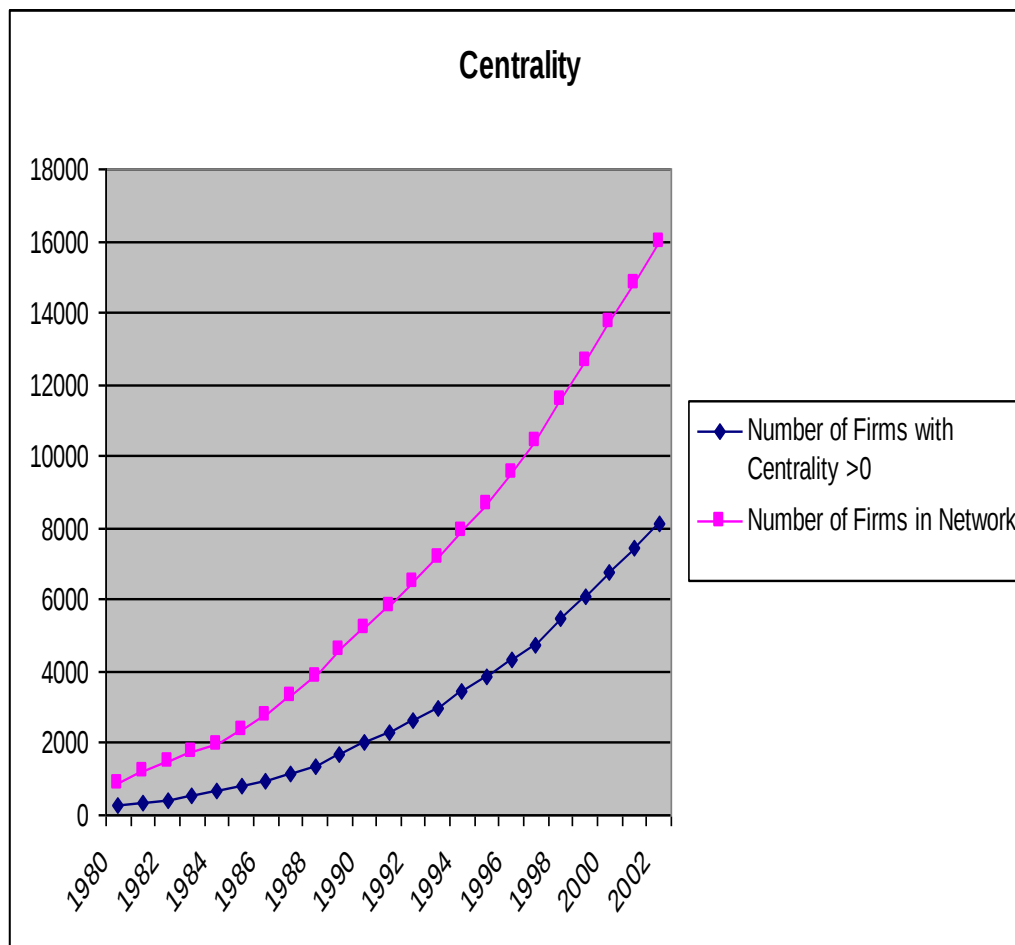


Figure 3. Contour Plot of Alliance Rate and Firm Classification



Constraint	High	Embedded Marginals	Embedded High Status
	Low	Low Status Brokers	High Status Brokers
		Low	High
		Status	

Table 1. Definition of Variables Used in the Study

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Table 2. Summary Statistics and Correlation Table of Variables

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Table 3. Fixed-Effect Negative Binomial Regression Results

DV	IV	(1)	(2)	(3)	(4)
Alliance	Constraint		-1.583** (0.631)	-1.347** (0.598)	-1.328** (0.594)
	Status			-0.000236*** (5.88e-05)	-0.000384*** (7.76e-05)
	ConstraintXStatus				0.00164*** (0.000511)
	Communityme	-0.0193** (0.00984)	-0.0180* (0.0102)	-0.0167* (0.00972)	-0.0157* (0.00940)
	Innovationimp	-2.35e-05 (2.06e-05)	-2.14e-05 (2.06e-05)	9.86e-05*** (3.40e-05)	9.03e-05*** (3.30e-05)
	Allianceexp	0.00127*** (0.000486)	0.00133*** (0.000483)	0.00149*** (0.000475)	0.00200*** (0.000493)
	TotalIPFlow	0.000371 (0.000232)	0.000338 (0.000233)	0.000292 (0.000230)	0.000359 (0.000223)
	Chem IP	-0.0120 (0.00861)	-0.0124 (0.00856)	-0.0165* (0.00866)	-0.0173** (0.00856)
	C&C IP	-0.0168* (0.00858)	-0.0170** (0.00851)	-0.0177** (0.00864)	-0.0171** (0.00855)
	EEE IP	-0.0159* (0.00929)	-0.0164* (0.00922)	-0.0183* (0.00936)	-0.0171* (0.00922)
	Mech IP	-0.0109 (0.0102)	-0.0107 (0.0102)	-0.00905 (0.0103)	-0.0125 (0.0103)
	Total KS IP	0.0149* (0.00807)	0.0151* (0.00801)	0.0154* (0.00812)	0.0156* (0.00805)
	yr90	0.126 (0.144)	0.130 (0.143)	0.132 (0.143)	0.137 (0.143)
	yr91	1.319*** (0.120)	1.310*** (0.120)	1.320*** (0.119)	1.322*** (0.118)
	yr92	1.679*** (0.117)	1.665*** (0.117)	1.665*** (0.117)	1.663*** (0.116)
	yr93	1.664*** (0.117)	1.642*** (0.117)	1.657*** (0.117)	1.651*** (0.116)
	yr94	1.611*** (0.118)	1.583*** (0.119)	1.586*** (0.118)	1.568*** (0.118)
	yr95	1.772*** (0.120)	1.739*** (0.120)	1.729*** (0.119)	1.700*** (0.119)
	yr96	1.592*** (0.126)	1.549*** (0.127)	1.539*** (0.126)	1.506*** (0.126)
	yr97	1.107*** (0.130)	1.062*** (0.131)	1.047*** (0.130)	1.029*** (0.130)
	yr98	1.197*** (0.127)	1.141*** (0.129)	1.206*** (0.128)	1.169*** (0.128)
	Constant	0.217 (0.141)	0.382** (0.154)	0.440*** (0.155)	0.452*** (0.155)
	Observations	1774	1774	1774	1774
	Number of firms	186	186	186	186
	Loglikelihood	-2746.75	-2742.78	-2734.44	-2729.86
	Wald χ^2	601.45***	611.40***	634.02***	655.17***
	Standard errors in parentheses				
	*** p<0.01, ** p<0.05, * p<0.1				

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