APPENDIX 4: LOCAL SEARCH BEHAVIOR IN A CORPORATE R&D CENTER: THE ROLE OF SOCIAL CENTRALITY AND TECHNOLOGICAL SPECIALIZATION[5]

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I am grateful for Dr. Jukka-Pekka Salmenkaita for providing the data on publications and internal reports filed by the employees studied in this research.

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LOCAL SEARCH BEHAVIOR IN A CORPORATE R&D CENTER: THE ROLE OF SOCIAL CENTRALITY AND TECHNOLOGICAL SPECIALIZATION[1]

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Abstract

Technological evolution is a gradual process, in which inventors re-apply existing ideas to create novel combinations. Prior research has suggested that firms tend innovate in familiar technological domains and do so by utilizing familiar solutions, i.e. exhibiting local search behavior. According to my hypotheses, social centrality (direct and indirect strong ties within the unit) and technological centrality (inventing in a technological domain important to the firm) increase the extent of local search. Since social networks can both help locate quick solutions and solve unfamiliar problems, their influence may be contingent on context. I find that social centrality increases local search in technological periphery, whereas it helps overcome local search in core technological areas. I further investigate conditions under which an invention is likely to become a source of subsequent technological development. Results indicate technological centrality and the moderate use of the firm's prior own knowledge to increase the internal impact of inventions. Somewhat surprisingly, I do not find a positive relationship between social centrality and subsequent intra-firm use of knowledge. These interrelations of social structure and technology partially open the black box of technological path-dependencies commonly presumed in evolutionary economics and typically observed on an organizational level.

[1] I am grateful for Dr. Jukka-Pekka Salmenkaita for providing the data on publications and invention reports utilized in this chapter.

1 INTRODUCTION

Technology development in companies is bounded by its existing knowledge, and follows a historical trajectory. Firms concentrate persistently on the familiar technological problem areas with, re-combining their existing knowledge to create new solutions (Helfat, 1994; Nelson & Winter, 1982; Stuart & Podolny, 1996). Recently, scholars have suggested that the tendency to utilize own prior technological solutions can have a detrimental effect on their ability to create valuable innovations when taken to the extreme (Ahuja, Galletta, & Carley, 2003; Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001), leading to lack of exploration and competency traps (Levinthal & March, 1993; March & Simon, 1993). Noting the importance of knowledge on innovative activities, scholars have explored how network relationships and structures within and across organizations influence the corporate research and development (R&D) activities (Nerkar & Paruchuri, 2005; Reagans & Zuckerman, 2001; Rosenkopf & Almeida, 2003; Schildt, Maula, & Keil, 2005).

Studies of local search in R&D have mainly investigated the dynamics on the aggregate level of organizational outcomes (Ahuja & Lampert, 2001; Katila & Ahuja, 2002). However, to be able to better understand and manage innovation activities in organizations, it is worthwhile to examine how these dynamics work at the level of teams (Reagans & Zuckerman, 2001). A more fine-grained analysis will allow us to elucidate the effects of social and technological structures leading to path-dependence. Focus on teams also complements and extends the prior studies which have focused on individuals (Burt, 2004; Nerkar & Paruchuri, 2005), as well as replicates the findings made on the firm level of aggregation (e.g. Katila & Ahuja, 2002). In addition to translating and replication of aggregate firm-level findings on team level, I utilize the more fine-grained level of analysis to extend the literature. Particularly, I examine how the technological specialization and social network structure influence local search behavior in innovation teams. I then investigate the conditions under which new inventions are the most likely to form a part a larger technological trajectory, becoming sources of subsequent invention.

In this paper I examine “innovation teams”, groups that have created a technological invention in a corporate R&D unit. My focus is on the effects of a team’s social centrality (based on prior collaboration patterns of team members within the R&D unit) and technological centrality (i.e. the prior volume of activity in the technological area the team is working in) on its local search behavior—the tendency of inventors to utilize corporation's existing prior own knowledge—and the subsequent impact of inventions. Since companies have greater stocks of knowledge in technological areas they are the most active in, teams working in central areas can re-use existing knowledge more easily to solve new problems. Similarly, teams located in a network of diverse social ties have access to a broad range of pre-existing knowledge created within the corporation (Burt, 2004; Burt, 1992); thus, they have less need to search for novel knowledge and greater incentive to use local knowledge.

However, conceptualizing networks as social resources that can be strategically utilized by the involved actors (Gulati, 1999; Padgett & Ansell, 1993) suggests a more complex influence. Social networks may actually help actors ignore existing knowledge and enable the creation of entirely novel solutions (Ahuja et al., 2003). Whether the network enables novel ideas to be pursued, or propagates existing ones is likely to depend on the technological area the team is working on. Within less central technological areas, networks are likely to be increase the availability of existing knowledge and help solve problems with prior own knowledge. However, in the most central technological areas, where own knowledge is more abundant, the social networks may in contrast mainly help develop entirely novel solutions.

After the examination of local search behavior by innovation teams, I examine factors that increase the likelihood that a team's invention becomes a source for subsequent technological development. I expect technological centrality to increase subsequent use of the piece of knowledge as investments into R&D tend to persist within the same areas (Helfat, 1994). The social centrality of the innovation team is likely to improve the quality of inventions (Burt, 2004; Reagans & Zuckerman, 2001), and thus the likelihood that they will be utilized in the future. The extent to which invention is based on the prior knowledge of the firm is likely to influence their subsequent use (Rosenkopf & Nerkar, 2001). Rosenkopf and Nerkar associate the use of internally developed knowledge with "competence traps" (Levinthal & March, 1993; Levitt & March, 1988); companies reluctant to search for new, superior solutions beyond the current knowledge stock of the firm generate sub-optimal inventions, leading to inferior performance. On the other hand, inventions that are radically different from a firm's prior inventions (Ahuja et al., 2003) are likely to be more difficult to adopt as a source of subsequent innovation. Since both extremes appear unbeneficial, the relationship between invention's use of prior knowledge and its subsequent internal impact is likely to follow an inverted-U shape (cf. Katila & Ahuja, 2002).

A unique data set covering all the inventions created within a research and development unit of a large multinational corporation allows me to examine the relationship between collaborative patterns and innovation characteristics. I find social centrality and technological centrality to be highly interrelated, even after accounting for alternative explanations. On average, centrality in social networks and technological areas increases the use of own prior own knowledge. However, in technologically central areas, social centrality actually helps teams overcome local search. Inventions create the greatest subsequent impact in organizational R&D when they address familiar problems (i.e. reside in central technological areas) and draw modestly on familiar solutions, building on both internal and external prior patents. My results do not support an earlier finding that central inventors would be more efficient in diffusing their inventions within the corporation (Nerkar & Paruchuri, 2005). Rather, post-invention centrality is negatively and significantly related to organizational impact.

2 THEORY

Empirical research has established the generic tendency of firms to persist in their technological inputs and outputs, thereby concentrating on particular technological areas (Helfat, 1994; Patel & Pavitt, 1997; Stuart & Podolny, 1996). As firms age, they repeatedly use their internally generated knowledge as a basis for solutions within these areas (Stuart & Sorensen, 2003). Recently, researchers have investigated how the extent of local search influence firm-level and innovation-level performance (Ahuja et al., 2003; Katila, 2002; Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001). I extend this literature by examining two structural factors likely to lead to local search: social ties within the R&D unit and technological specialization.

Firms' decisions about which technologies to develop are greatly bounded by prior organizational routines as well as by their employees' knowledge (Nelson & Winter, 1982). The skills, experience and knowledge held by individuals working in a research and development unit are typically slow to change. Moreover, the knowledge related to a technological area is likely to accumulate within a technological paradigms (Dosi, 1988). Each employee is likely to specialize in a limited number of technological areas, obtaining knowledge pertaining to the prevalent technological paradigm. As long as employees are not hired and laid off in great numbers, the firm's competence areas persist. Therefore, the choices companies can make regarding their technological development efforts are limited. This is especially problematic for firms aiming to create novel break-through innovations. Since new inventions "evolve" through recombination of pre-existing knowledge (Fleming & Sorenson, 2001; Nelson & Winter, 1982), the prevalent knowledge stocks also influence the type of unplanned technological inventions created by the employees.

The social structure of the research and development unit also represents an important context for innovativeness. Schumpeter's definition of innovation as a novel combination of pre-existing knowledge is now broadly accepted (Nelson & Winter, 1982). As a direct implication of this view, scholars have emphasized social networks in explaining the ability to solve technological problems and innovate (Aiken, Bacharach, & French, 1980; Allen, 1977; Burt, 2004). The networks within which a firm's inventors are embedded influence the flow of information and access to knowledge, both factors that affect propensity to generate new ideas and characteristics of resulting inventions. Earlier research has suggested that technological solutions tend to diffuse through networks (Burt, 1992). Especially densely connected networks are likely to increase the spread of similar problems and solutions, inhibiting the creation of radical ideas (Burt, 2004).

2.1 Social networks and specialization

Strong social ties are formed across individuals who work together on the same projects. Collaborative ties form a durable structure of mutual acquaintance, which may act as a conduit for information and an aid in problem solving (e.g. Allen, 1977). Over time, employees may work with a broad range of individuals or they may repeatedly collaborate with a limited number of colleagues.

Social network ties tend to form around people who are similar (McPherson et al., 2001). In a research and development setting, technological specialization is thus likely to influence the formation of networks. Employees who work in the same technological area are more likely to interact. As a consequence, teams working in central technological areas are likely to have a larger number of network ties, whereas teams working in less central areas are likely to have a lower number of peers, and thus lower social centrality. The social centrality of any project team and the technological area it invents in are likely to be co-determined by the general dynamics of team formation and social network formation. As a result, we can hypothesize:

> ***Hypothesis 1a:*** *Socially central teams are more likely than socially marginal teams to generate inventions in central technological areas.*
>
> ***Hypothesis 1b:*** *Technological centrality of the team tends to be associated with social centrality.*

It is worth noting that these predictions are based on an association, not a causal mechanism. The association arises out of the multiple common rationales which R&D unit management use to compose project teams. Some teams can be based on serendipitous ideas arising from informal communication among to-be team members; some are composed to carry out planned efforts to solve pressing technological problems or to commercially exploit new scientific research. Since team formation results from endogenous choices with no single uniform patterns, it seems unwise to hypothesize simple causal determinants for social and technological centrality.

2.2 Local Search in Technological Innovation

Prior research has shown that firms have a strong tendency to utilize prior internally developed knowledge as a source of subsequent technological development (Rosenkopf & Nerkar, 2001; Stuart & Sorensen, 2003). Sorensen and Stuart propose that as organizations age, they are increasingly likely to engage in such local search behavior. While I am not aware of any research that would have specifically examined team-level predictors of technological local search, firm-level findings provide cues for team-level dynamics. According to behavioral decision making theory, local search is likely to result from the availability of familiar and readily usable solutions (Cyert & March, 1992). I suggest two major predictors for the use of local solutions for the problems addressed by an innovation team: broad social network and specialization in a central technological area.

Earlier research strongly indicates that the centrality of inventors in a social network is likely to influence local search tendency. Given that strong network ties enable knowledge transfer within a corporation (Hansen, 1999), individuals who are central in social networks are able to solve technological problems by drawing on the company's existing local knowledge (Reagans & Zuckerman, 2001). I thus predict that the broader the set of ties an innovation team has with the other members of the research and development unit, the more likely it is to identify and successfully exploit prior inventions as bases for new knowledge creation (Minzberg, Raisinghani, & Thêorêt, 1976).

The second factor, specialization in an organizationally central technological area, needs little explanation. A team that develops solutions within the area where a company has the greatest stock of pre-existing knowledge is also best positioned to usefully apply the firm's earlier ideas. Since the existing products and hence the greatest existing markets are based in core technological areas, there are also greater economic incentives for exploitative, incremental inventions within the technological core.

> ***Hypothesis 2a:*** *Social centrality of an innovation team leads to greater use of prior own knowledge in the invention.*

> ***Hypothesis 2b:*** *Technological centrality of the innovation team leads to greater use of prior own knowledge in the invention.*

Although the above suggests that both technological and social centrality may independently increase the likelihood of local search, social networks may actually exhibit a reverse effect. If we conceptualize networks as resources that are strategically utilized by the actors (Padgett & Ansell, 1993), the influence of networks should be seen as potentially context-dependent. Networks can act not only as conduits for prior solutions; they can also facilitate the creation of entirely novel ideas (Ahuja et al., 2003; Powell, Koput, & SmithDoerr, 1996). This is particularly likely in the important core areas of the company, which are normally prone to incremental inventions. The most socially connected teams may be able to utilize their network ties to create radical solutions that overcome local search, renewing the technological core competencies of the corporation. Since less central technological areas provide auxiliary technologies (Brusoni, Prencipe, & Pavitt, 2001), they have lesser influence on a firm's competitive advantage than central technological areas. Socially central teams may thus try to maximize the use of prior knowledge in non-central technological areas. However, in central areas in which prior knowledge is more abundant, networks may be used to develop entirely new solutions, or at least the benefits of networks as sources of prior solutions are mitigated due to greater availability of applicable prior solutions.

> ***Hypothesis 2c:*** *The positive influence of social centrality on the use of prior own knowledge is decreased in more central technological areas.*

2.3 Subsequent innovation impact

Social and technological centrality are likely to also influence the likelihood of inventions becoming sources of subsequent technological development within the company. Given the prevalence of local search behavior, technological centrality is likely to significantly increase the future impact of an invention. Given the gradual and persistent evolutionary nature of research and development efforts (Helfat, 1994), the more central the invention's technological area, the more likely there will be related inventions in the future (Podolny & Stuart, 1995). Probabilistically, inventions in central areas within the organization provide a basis for a wider range of future solutions compared to inventions in marginal areas.

> ***Hypothesis 3a:*** *The more central the technological area of an invention, the higher the impact it will have on subsequent technological development within the firm.*

Second, the extent of the social networks of the innovation team's members at the time of the invention influence internal impact. Prior research suggests that the average quality of inventions created by individuals with a broad set of social ties should be superior to those created by narrow set of social connections (Burt, 2004; Reagans & McEvily, 2003). Similar argumentation has also been applied to teams (Reagans & Zuckerman, 2001). The superior quality results from the greater breadth of useful information and solutions available to well-connected teams. To the extent that subsequent impact on research and development activities reflects the quality of inventions, central teams are bound to have on average a higher impact. In addition to increased quality, networks may also propagate the knowledge regarding the invention within the firm. Social networks act as conduits of knowledge, making other relevant inventors more likely to hear about the invention (Coleman, Katz, & Menzel, 1957) and consequently concentrate their future work efforts on similar issues (Nerkar & Paruchuri, 2005).

> ***Hypothesis 3b:*** *The more socially central the innovation team is at the time of the invention, the higher the invention's subsequent internal impact of the invention.*

Finally, earlier research has suggested that companies that utilize their own prior knowledge moderately are more productive in terms of new product introductions in comparison to companies with either very high or very low use of prior own knowledge (Katila & Ahuja, 2002). Rosenkopf and Almeida (2001) found that the sole use of prior own knowledge reduced the external impact of inventions (although the authors did not test curvilinear effects). Katila and Ahuja suggest that moderate use of one's own prior own knowledge leads to optimal benefits, as the company exploits its own core competences but also simultaneously adopts ideas invented beyond its boundaries. Although the argumentation is made on the aggregate level of the whole technological portfolio and firm performance, there are reasons to believe that moderate use of prior own knowledge on the level of individual inventions would lead to easier adoption of ideas as a basis for subsequent development. Local search results in inventions that are similar to existing technology and thus familiar to other employees and more easily transferred to the other teams (Cummings & Teng, 2003; Reagans & McEvily, 2003). However, inventions building solely on internal knowledge may result in dead-ends: inventions that are of little use as a basis for new ideas.

> ***Hypothesis 3c:*** *The extent to which an invention utilizes prior own knowledge has an inverted-U relationship with the subsequent internal impact of the invention.*

3 EMPIRICAL SETTING AND METHODOLOGY

To investigate the effects of specialization and social networks on innovative activities, we studied the corporate R&D unit of a large global corporation operating in the electronics and telecommunications industry. Our primary data is from mandatory invention reports filed by the employees of the R&D unit and subsequent successful patent applications the company has made based on the invention reports. The company studied here uses invention reports by research scientists and engineers to formally document any potentially patentable inventions. The reports indicate collaborative connections between employees in the R&D unit; thus, co-authorships represent strong pre-invention network ties between employees of the unit. Scientists in the R&D unit also collaborate on manuscripts published in conferences and scientific journals. To capture these strong ties between individuals we collected all scientific articles authored by the employees of the R&D unit. Bibliometric data was downloaded from ISI Web of Science database, maintained by Thomson Scientific. I merged ties from co-publications and co-authored invention reports to form a network of interpersonal strong ties. Both invention reports and scientific articles included ties to the employees of the R&D unit and other business units, as well as researchers from universities and government research laboratories. I used a moving three year window prior to the invention to construct the network measures.

The corporation also provided me with access to its extensive database, which provides details of its patents that result from invention reports. Reliable data was available from 1995 onwards. This data allowed me to link innovation teams with invention characteristics, derived from patent data (e.g. Rosenkopf & Nerkar, 2001). I also obtained all patents filed by the corporation and its subsidiaries from 1981 to August, 2004 from the MicroPatent online database. Historical patent data, filed prior to and cited in an invention report, provides a basis for the measurement of local search, whereas subsequent patents and pending patent applications provide a basis for measuring the impact of the inventions on the R&D activity of the company following the focal invention by the team.

As patents are relatively expensive to file and protect, inventions with a low commercial potential may be underrepresented in the sample. Such limitations, however, are unavoidable in patent-based research (Podolny & Stuart, 1995). In contrast to studies that utilize collaborative networks through patent co-authorship (Minzberg et al., 1976; Nerkar & Paruchuri, 2005), the use of invention reports and publications provides a more complete map of the relationships. For the reliable measurement of invention impact, and social networks, I had to limit my study to inventions that were created within the research and development unit from 1995 to 1999.

3.1 Key variables

The hypotheses posit several variables (social centrality, technological centrality, and prior own knowledge) as both dependent and independent variables in alternative regression models.

Technological centrality reflects the amount of prior development work done by the company in the technological area to which the patented invention belongs. Arguably, areas of expertise in which the company has filed thousands of patents in are central to the operations (the corporation was granted 500-1000 patents yearly during the observed period). In contrast, patents in areas in which only a dozen prior firm patents exist are either exploratory, resembling potential directions in firm's technology strategy (March & Simon, 1993), or auxiliary technologies that support core operations (Brusoni et al., 2001).

This measure is constructed by calculating the number of patents the firm had filed in a focal invention's patent class in preceding years (from the year 1981 onwards) in thousands. When a patent belongs to multiple classes, I average the total volume of prior patenting activity within those classes. The patent classes are distinguished by the first four characters/digits of the international patent classification (IPC) codes. The classification scheme is based on the type of technological knowledge utilized in the invention and the functional purpose of the invention. The scope of the most technologically intensive areas tends to grow over the study period, an effect controlled for by year dummies.

Social centrality. Although there exists a broad range of options for measuring an actor's centrality in a network (Wasserman & Faust, 1994), it is not clear how to best measure centrality of a research team. Past studies have used a centrality measure for the most central individual within a team (Nerkar & Paruchuri, 2005). This solution, though viable, does not distinguish whether a team members have heavily overlapping social ties or are broadly connected to disparate others. To overcome these shortcomings, I experiment with a somewhat novel measure of the social connectedness for the team, drawing on Bonancich's idea that centrality is best measured not only by the multiplicity of an actor's ties, but also the centrality of the alters the actor is connected to (Bonacich, 1987).

The measure for team social centrality used in this study is the number of unique contacts within the R&D unit to whom team members are connected either directly or indirectly (through one shared connection). The connections are determined based on the invention reports filed and scientific or technical articles published within the three years preceding the invention. Since the measure captures non-overlapping social ties, it indicates the breadth of the team's social network among other technical and scientific personnel within the research and development unit.

Local Search. Companies vary in their tendency to develop technological inventions that build on, or are related to, their prior own knowledge (Rosenkopf & Nerkar, 2001; Stuart & Sorensen, 2003). This practice, commonly characterized as local search (Rosenkopf & Nerkar, 2001), has almost universally been measured by counting the citations a firm's patents make to its prior patents, i.e. in terms of self-citations (Katila & Ahuja, 2002; Rosenkopf & Nerkar, 2001; Stuart & Sorensen, 2003). I use the same approach, defining the use of prior own knowledge as the percentage of all citations that reference the corporation's prior patents (represented by a value from 0 to 100). In the rare case where a patent cites no prior patents (16 observations) I assigned the variable value 0. I also verified that results remain similar when these observations are removed from the sample.

Internal impact of inventions is measured as the number of citations the invention receives from the subsequent patents and patent applications filed by the corporation up to August 2004. Received citations have been found to correlate with expert opinion on patent value (Hall, Jaffe, & Trajtenberg, 2000). Moreover, by focusing on the corporation's self-citations one can evaluate the diffusion of inventions and most crucially, the extent to which an invention becomes a source of subsequent local search. Patent citations are made only to prior inventions that are critical to the patent, and their use is governed by patent officials. Consequently, a patent receiving numerous citations reflects an invention that has created, or at least enabled, a trajectory of further technological development.

Since the measure is subject to right censoring (there are likely to be future patents that will create further citations) the year dummies are instrumental in correcting the systematic differences in impact of patents filed in the beginning and in the end of the study period.

3.2 Control variables

Control variables account for team- and invention-specific factors that could cause considerable bias to the models.

Team size equals the number of members from the R&D unit that participated in filing the invention report. A large team is likely on average to have a larger social network than a smaller team. Quite likely, projects the firm considers to be of high importance are systemically assigned more personnel. Given that team size can be adjusted based on the perceived importance of the particular technological problem being solved, it might be a cause for the team's social centrality, technological centrality, and the subsequent impact of the invention.

Average team member tenure reflects the experience of the team. Teams including experienced employees might be more likely to create high-impact inventions simply due to greater technological expertice. Also, since organizational tenure has been suggested to improve performance (Reagans & Zuckerman, 2001) and breadth of networks is likely to increase over time, effects of tenure might be falsely attributed to social centrality if they are not controlled for. This is measured as the average years since team members filed their first innovation report or publication in the R&D unit. Since the data on publications and innovation reports is only available from the beginning of 1990s, this measure is likely to be censored. Nonetheless, it helps distinguish between experienced and recently employed personnel.

Prior innovations measures the past productivity of the team as the total number of unique prior invention reports filed by all members of the team. Teams that include experienced innovators might be more likely to create high-impact inventions simply due to greater human capital. Also, the breadth of a person's social network ties can be linked directly to the extent of the person's prior work and productivity within the organization – especially given that networks are measured by explicit outcomes (scientific or technical papers and joint innovations). Because more capable and innovative individuals may attract more network contacts, we might observe a false reverse causality between social capital and invention impact if we fail to control for team-level competence.

Patent scope reflects the breadth of knowledge cited in the patent. We include this variable to control for potential correlation between use of any prior patented knowledge and the use of prior own knowledge. Patents that have little relation to earlier patented knowledge are likely to make relatively modest (or narrow) claims. In contrast, patents with numerous citations may contain a broader set of ideas and thus more likely to be cited by subsequent work. Accounting for invention scope allows us to more robustly measure local search and the subsequent impact.

Academic collaboration. Some of the projects in the R&D unit were created in collaboration with universities. Such projects might be systematically different from internal projects. In particular, such inventions could be considerably more novel and also create a greater (or lower) impact within the organization. I did not want to exclude inventions formed in collaboration entirely, and thus I control for the possibility that the access to external experts could create substantial effects. The variable receives value 1 if the invention in question was done in collaboration with a university, and 0 otherwise.

Year dummies. In addition to these control variables, I also controlled for the invention year. As we expect earlier patents to have received more citations than newer patents, earlier invention years should show significant positive effects on patent impact. Moreover, the technological core of the firm might mature, reducing the novelty of latter inventions. Year dummy effects are relative to the year 1995, which is included in the constant term.

3.3 Some observations regarding the relationship between patents and inventions

Some invention reports are linked to multiple patents. Indeed, there is a notable degree of variation in patent scope and the number of claimed novel ideas across patents. What some could consider a single invention may be captured by a varying number of patents; in other cases one patent may protect multiple inventions. Although most research often equates patent documents with individual inventions, patents may contain multiple, relatively independent and even unrelated claims. In other instances, an invention report resulted in relatively similar patents within U.S. and E.U. These patents often had great overlap in their citations.

It would be inappropriate to consider each patent to represent a separate invention, as there is a considerable question of non-independence of observations. Moreover, an interview with a senior member of the corporate R&D unit suggested that invention reports, which are used internally, are a more valid measure of independent inventions than are patents, which are strategically utilized legal documents. Consequently, I pooled multiple patents relating to one invention report and averaged the measures for the use of prior own knowledge. The pooling procedure did not alter the measures significantly, as the citations from U.S. and E.U. patents mostly overlapped. I combined all unique citations from these patents to construct citations-related measures. Also, I measured an invention's internal impact as the number of unique subsequent patents that cited as least one of the patents associated with the invention report. I verified that controlling for the number of patents associated with an invention report did not materially change the results.

3.4 Model specification

I first utilize ordinary least squares linear regression models to examine social and technological centrality. The third model models the share of prior own knowledge using the Tobit regression model. Share of prior own knowledge is bounded to lowest value of

0 and highest value of 1. The Tobit model is suitable for such cases of a censored dependent variable. Finally, I use a negative binomial regression model to account for the internal impact of inventions. The invention impact is captured by the count of subsequent citing patents, and thus requires a probabilistic model. Although it is customary to use Poisson regression models for count data, there was over-dispersion in our sample and the negative binomial model was more appropriate. Heteroscedasticity is controlled by using robust estimators in the statistical software package *Stata*.

3.5 Descriptive statistics

The descriptive statistics and correlation coefficients for dependent and independent variables are presented in Table 1. As expected, social and technological centrality correlate significantly (coefficient 0.28). Also, control variables accounting for team size, average organizational tenure, and prior innovation output are all strongly correlated with social centrality.

Table 1: Correlation coefficients and descriptive statistics

	Mean	S.D.	Min.	Max.	(1)	(2)
1. Technological centrality	.73	.58	0	2.82		
2. Team social centrality	18.07	24.11	0	89	.27 ***	
3 Local search (%)	15.13	21.95	0	100	.13 **	.13 **
4 Internal impact	2.10	3.52	0	30	-.07	-.06
5 Team size	1.70	.88	1	6	-.01	.19 ***
6 Average tenure	1.11	1.18	0	9	.24 ***	.57 ***
7 Prior inventions	6.68	9.43	0	57	.21 ***	.84 ***
8 Academic collaboration	.01	.10	0	1	-.07	-.01
9 Patent scope	8.32	6.00	0	40	-.23 ***	-.03
	(3)	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
4 Internal impact	.01					
5 Team size	-.02	.03				
6 Average tenure	.06	-.06	-.01			
7 Prior inventions	.06	-.08	.28 ***	.49 ***		
8 Academic collaboration	-.03	-.05	-.01	.02	-.02	
9 Patent scope	.11 *	.26 ***	.13 **	-.09 +	.01	.07

450 observations. *** p<.001; ** p<.01; * p<.05.

Table 2: Regression results

	1. Technological centrality[a]	2. Social centrality[b]	3.Local search[c]	4. Internal impact[d]
Independent variables				
Technological centrality		3.37 **	24.17 ***	1.56 **
		(1.17)	(4.49)	(.22)
Social centrality	7.64 ***		.97 ***	1.00
	(2.32)		(.20)	(.02)
Social * Technological centrality			-0.60 ***	
			(.15)	
Local search (%)				1.01 +
				(.01)
Local search^2				.98 *
				(.01)
Control variables				
Team size	-5.27	-.57	-1.20	1.05
	(29.41)	(.66)	(2.19)	(.09)
Average tenure	-4.19	3.96 ***	.56	1.11
	(26.61)	(1.05) ***	(1.98)	(.11)
Prior inventions	-2.45	1.87	-0.70 +	.99
	(4.66)	(.13)	(.37)	(.01)
Academic collaboration	-356.66	.38	-16.27	.30 *
	(233.93)	(3.07)	(18.61)	(.18)
Patent scope			1.18 ***	1.04 ***
			(.32)	(.01)
1996	83.44	2.73 **	-6.66	.88
	(84.76)	(1.01)	(6.40)	(.20)
1997	218.87 **	1.01	-1.64	.47 **
	(86.45)	(1.39)	(6.59)	(.12)
1998	386.94 ***	1.39	-13.43 +	.33 ***
	(89.17)	(1.68)	(7.13)	(.09)
1999	676.24 ***	-.62	-19.52	.26 ***
	(91.26)	(1.57)	(7.67)	(.08)
Constant	377.36 ***	-1.34	-19.08	
	(82.42)	(1.29)	(7.27)	
Observations	450	450	450	450

All models are significant at p<.001. I utilize one-tailed tests for independent variables and two-tailed tests for controls.

[a] Linear regression model (ordinary least squares). The dependent variable is multiplied by 1000.

[b] Linear regression model (ordinary least squares).

[c] Tobit regression model with censored upper (1) and lower (1) bounds. Team social centrality is divided by 1000 for this model to scale coefficients.

[d] Negative binomial count data model. Coefficients reported as incident rate ratios.

*** p<.001; ** p<.01; * p<.05

4 RESULTS

Table 2 presents the results of the study. As is typical in regression analyses, I also tested reduced models that included only control variables and then entered independent variables and interaction terms independently. To conserve space, these reduced models are not presented. All independent variables have similar significant effect when the interaction terms are not included.

Models 1 and 2 depict the covariance of technological and social centrality, accounting for alternative sources of association (e.g. team tenure and number of prior inventions). The models show significant support for Hypotheses 1a and 1b. Socially central actors tend to form teams that work on central technologies. It is worth repeating at this juncture that the models do not depict a causal relationship between technological and social centrality. Instead, I suggest that heterogeneous social processes lead to the formation of teams in which these particular characteristics tend to correlate.

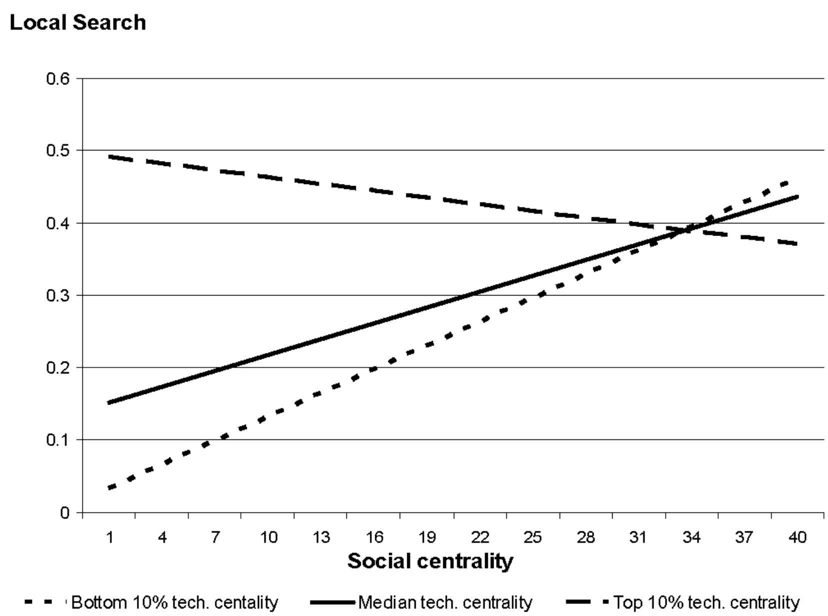

Figure 1: Effects of social centrality on the extent of local search, moderated by the centrality of the technology. The graph is based on regression results in Model 4 of Table 2.

The third model depicts the effects of social and technological centrality on the extent of local search, using Tobit regression. The findings provide support for Hypotheses 2a, 2b, and 2c. As predicted, both social and technological centrality increase the likelihood that teams draw on prior own knowledge (i. e. resort to local search) while developing inventions. Moreover, socially central teams tend to utilize local search less when working in central technologies and more when working on peripheral technology. Likewise, socially less central teams resort to local search especially when working in core technological areas. This relationship between social and technological centrality is depicted in Figure 1.

The fourth model shows the effects of social and technological centrality and local search on internal impact of inventions. As predicted in Hypotheses 3a, the model shows that technological centrality is associated with higher subsequent impact. However, I am unable to find a positive association between team's social centrality and subsequent impact, as predicted in hypothesis 3b. The social centrality of the team at the time of invention has no statistically significant impact on received citations.

Finally, Hypothesis 3c predicted that local search would have an inverted-U relationship to the subsequent impact of inventions. Although the first order term is not significant, the shape resembles an inverted U (see Figure 2) since quadratic term is negative (below 1.00 when represented as IRR) and significant. Since the distribution for the use of prior own knowledge was skewed, I ran several robustness tests to evaluate the shape of effects. The sub-sample of inventions whose share of citations to prior own knowledge is below 20% shows a significant positive relationship between prior own knowledge and subsequent citations, providing additional support for the inverted-U relationship. Inventions that moderately utilize prior knowledge are the most likely to gain subsequent citations and thus become sources for future technological development. The interpretation assumes that all other factors are held constant. Since greater local search is also associated with higher technological centrality in the sample, inventions with build heavily on own prior knowledge may nonetheless have high impact.

I would finally like to draw attention to the somewhat puzzling but significant relationship between academic collaboration and invention impact. According to Model

4, patents produced by the research and development unit in collaboration with university scientists yielded on average only 30% of the impact of similar inventions with no university collaboration. It is possible that this finding results from the relatively short time span utilized to measure subsequent impact (5-9 years). Academic collaboration might lead to more explorative and risky inventions that create broad impact only in a longer term. Also, it is likely that the corporation had avoided conducting their most strategically valuable research projects in collaboration with universities, given the risk of knowledge leaks, suggesting an endogenous explanation.

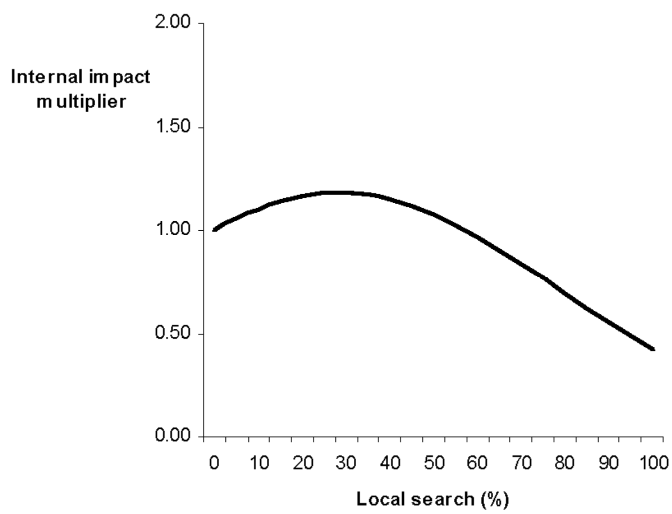

Figure 2: Relationship between self-citations and subsequent internal impact of inventions. The graph is based on regression results in Model 4 of Table 2.

5 CONCLUSION

In this study I examined the determinants of the novelty and impact of inventions in industrial research, focusing on technological and social centrality of innovation teams. Although several firm-level studies exist, this is the first study to examine the joint effects of social and technological centrality on local search tendency and also the first to account for invention-level effects. As a result, the study makes several contributions for management research on firm innovation activities.

First, I find that social centrality of R&D employees is strongly related to their area of specialization. Teams that focused on technological areas where the company was most active tended to have broader social networks. This finding has clear implications for future network studies of R&D: effects of network centrality may partially be created by specialization. Prior studies of inter-organizational networks have provided an analogous finding: firm-level specialization in central technological areas fosters creation of networks within an industry (Stuart, 1998). The relationship between networks and specialization also has potential implications for technological strategy, as technologically diversified companies might have more diverse networks. Since network diversity is found to be beneficial (Burt, 1992), strategic decisions to diversify in R&D may create network-related advantages.

Second, I find that technological and social centrality individually predict local search, but inventions by socially central teams in technologically central areas tend to utilize less local search. This relationship demonstrates the duality of network outcomes: on one hand extensive networks provide easy pre-existing solutions, on the other they enable the creation of novel solutions. My findings suggest that use of networks may depend on the perceived strategic importance of the problem. Instead of simply providing direct probabilistic influence on outcomes, network structures could be seen as resources which actors can utilize strategically, depending on their goals (Gulati, 1999; Padgett & Ansell, 1993). Networks provide both quick solutions and access to resources that help create radical departures.

Third, I examine the relationship of social and technological factors to the subsequent impact of inventions within the company. I replicate pre-existing firm-level findings regarding local search behavior on innovative output, now on the level of individual inventions: the use of prior knowledge has a curvilinear (inverted-U) relationship to the subsequent impact of the invention. As a logical consequence of the common persistence of R&D focus areas (Helfat, 1994), I find that technological centrality is a significant predictor of subsequent invention impact. However, I fail to find a significant relationship between social centrality and subsequent impact.

Together these findings reveal some of the organizational dynamics underlying technological evolution. Persistence on same technological domains and solutions is driven by high-impact inventions that address existing technological problems by combining prior internally developed knowledge with external knowledge. Breadth of social networks has a complex relationship to path-dependence: although social networks tend to reinforce the use of existing knowledge by enabling local search behavior, they enable teams working in the most central technological areas to create inventions that overcome local search.

This paper opens some avenues for future research. First, future research could explore technological specialization more broadly. Patent data allows researchers to examine the areas of technological specialization for each inventor. Thus, we could examine how the combination of employees with similar or different technological backgrounds in a team influences the novelty and impact of resulting inventions. While I find that technologically central teams are more prone to utilizing the firm's prior own inventions and to attracting future citations, this study provides only limited insight into the organizational value of inventions. According to a recent study, neither self-citations nor received citations are strongly associated with radical break-through inventions (Dahlin & Behrens, 2005). Future research should thus examine the joint effects of local search and technological centrality on the commercial impact of inventions.

More broadly, the finding that the effects of network ties on local search behavior are contingent on technological centrality suggests that structural network analysis might benefit from a pragmatist approach. Network structures could be conceptualized as resources that actors can deliberately utilize in different ways, depending on the context and their objectives. In the behavioral decision making literature and in theoretical work related to local search tendency in particular, researchers have generally assumed the strategic goals of actors to be an outcome of search processes (Cyert & March, 1992; Levinthal & March, 1993). However, in the context of technology development, we might benefit from taking context-specific strategic imperatives as exogenous givens and observing how they affect the search processes.

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