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The organization of R&D work and knowledge search in intrafirm networks

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Abstract

This study investigates the effects of the organization of industrial Research & Development on industrial researchers' knowledge acquisition behavior. Specifically, we test a model about how the fit of individuals with their research tasks affects whether industrial researchers acquire knowledge from outside their assigned projects. Empirical analyses from the R&D laboratory of a global pharmaceutical company show that person-task-fit has a non-linear effect on the knowledge content exchanged through interpersonal interactions. Implications for the management and organization of R&D activities are discussed.

JEL classification: O32; D83; O31

1. Introduction

By presenting firms with increasingly unpredictable workstreams and by involving workers in the co-design of the organization alongside managers, contemporary contexts of management alter our understanding of how firms can achieve coordination and motivate their employees (Raveendran *et al.*, 2020). This is nowhere more clearly manifested than in industrial R&D settings, where organizations seek to manage and direct the transfer of knowledge (Allen *et al.*, 2007) but find that for that transfer, they are largely dependent on the agency of their members (Grigoriou and Rothaermel, 2013; Li *et al.*, 2013) and that their organizational structures and systems often hinder rather than facilitating those individuals (Criscuolo *et al.*, 2014).

This kind of issue has encouraged the start of a nascent stream of research on the influence of organizational design choices on knowledge search and work in corporate R&D (Argyres, 2018; Gambardella *et al.*, 2020; Soda *et al.*, 2021). A key premise for it is the theory and evidence that more connected networks make the location of knowledge and its subsequent recombination easier, thereby positively affecting innovative outcomes (Paruchuri and Awate, 2017). Accordingly, that literature has focused on how certain organizational features such as centralization, and the assigned roles of R&D units in the division of work, can restrict communication channels and mandate specific directions of search (Argyres *et al.*, 2020) or otherwise affect the researchers' costs and benefits of search on interpersonal advice networks (Brennecke *et al.*, 2021).

As those contributions focus on macro-organizational variables that affect all the workers in the organization—or groups of workers—in the same way, they rest on the implicit assumption of homogeneity of individual responses to managerial and design choices. However, on account of the importance of individuals in the knowledge search process (Dahlander *et al.*, 2016), and of the fact that certain parts of the search process require judgment rather than automatic responses to stimuli (Posen *et al.*, 2018), it is necessary to also consider managerial decisions that affect the more proximate work environment of R&D professionals and how individual cognition mediates the responses to those decisions. Indeed, R&D management is discovering the importance of job design (Gambardella *et al.*, 2020), and cognition has begun to seep into the study of individual search via ideas such as attention (Dahlander *et al.*, 2016).

To address these needs, we draw attention to the organization of *work* in the context of R&D projects. Integrating the organizational behavior concept of person–job fit (Edwards, 1991), with goal framing theory (Foss and Lindenberg, 2013; Lindenberg, 2013), and theoretical mechanisms about the effect of prior learning on individual knowledge search (March, 1991; Arts and Fleming, 2018), we predict a pattern in knowledge search behavior on interpersonal intra-organizational advice networks. Specifically, we predict that the fit between an individual's abilities and the task of the project to which the individual is assigned (the person–task fit (PTF)) will have an inverse U-shaped effect on the search from other R&D projects, conceptualized as problems and hypotheses of solutions—i.e. as problems and their required knowledge domains. Hence, our explanandum ("intra-project" vs. "cross-project" search) is conceptualized in line with the traditional local/distant distinction about the locus of search, though contextualized to industrial R&D project-based firms, and expanded to take into account that search behavior can be meaningfully characterized not only by the solutions it seeks but also by the problems it explores (Posen *et al.*, 2018). As to the mechanisms underlying such a pattern, we argue that the project organization presents researchers with multiple task-related objectives, characterized by different degrees of abstractness, and horizons of different remoteness and that the PTF can act as a relevant situational factor, capable of making those goals differently salient for different individuals, thereby influencing individual expectations about the costs and benefits of searching other projects for knowledge and problems.

We test our hypotheses using survey and archival data on 766 scientific and technical advice interactions among 93 industrial researchers working in the corporate R&D center of a large pharmaceutical company. Although we use standard network research methods to capture the advice relationships, we focus on the content that flows through those conduits (intra-project or cross-project problems and solutions), in line with the focus of recent literature (Sosa, 2011) and with calls from recent network research (Borgatti *et al.*, 2014). We find results that support our expected relationships.

Our study makes two main contributions to scholarly research. First, by considering the role of goal framing, we present a more realistic model of knowledge search, which is relevant, given how important attention processes are in individual decision-making and motivation (Ocasio, 2011) and how important individual search is for knowledge transfer and invention (Maggitti *et al.*, 2013; Dahlander *et al.*, 2016). Second, we add to the emerging literature on the influence of managerial and organizational design choices on knowledge search and transfer in industrial R&D (Clement and Puranam, 2018; Argyres *et al.*, 2020; Gambardella *et al.*, 2020; Brennecke *et al.*, 2021) by highlighting an explanatory factor that is impacted upon by the organization of work. By focusing on the fit between the task demands of an individual's assigned project, and the abilities that the person can muster, we attend to a factor that is closely akin to the main predictor of recent research on individual innovative behavior (Kwon and Kim, 2020) although we focus on at an outcome not considered in that literature. Compared to the roles of units in task collaboration or to the loci of budget allocation, our perspective draws the attention to a variable that is situated at a more micro-organizational level.

2. Theory development

2.1 The organization of industrial R&D: projects, goals, knowledge types

2.1.1 Research projects and the parsing of goals

Industrial R&D is usually organized around projects (Brown and Eisenhardt, 1995). Arguably, the most fundamental way in which the project organization affects individual knowledge search is through the assignment of goals to project researchers. The logic of projects is based on an orientation to actions (execution) rather than to decisions (Lundin and Soderholm, 1995). Due to the challenge of pursuing distant goals as those of basic or applied research usually are, such logic requires that "distal" (Locke and Latham, 1990), long-term outcome-level goals for the project (e.g. developing a novel and impactful solution to a technological problem) be also supplemented by the setting of "proximal," shorter-term operational goals about specific actions (e.g. in drug discovery, screening libraries of chemical compounds against therapeutic targets).[1] Evidence of long-term goal segmentation into several more immediate subgoals can be found in joint R&D collaboration contracts, which often state the goal of a collaboration in general terms while also specifying a number of specific subtasks to be performed for that purpose, stating these in terms of activities to be performed and associated deadlines—i.e. as proximal goals (Grandori and Furlotti, 2009).

2.1.2 Tensions between distal and proximal goals

Although in idealized descriptions, the relationship between proximal and distal goals is just one of sequential interdependence, whereby attaining goal A is a step for attaining goal B, in reality, the relationship is more complex.

First, operational goals generally have a greater motivational strength than distal ones (Sun and Frese, 2013). Second, distal and proximal goals compete for attention (Anderson, 1983). When investigating scientists and other professionals who pursue goals that span many years, Bateman and Barry (2012: 995) found clear support for this claim: "we actually have so many short-term goals that it is very hard to think about that long-term goal… it's not something that's right at the top level all the time." Organization theory and complex decision-making studies have been aware of tensions of this kind for a long time (Simon, 1960; Dörner and Schaub, 1994). Third, in technology innovation and science, it is often rational not to assume that operational-level research activities should keep aiming exclusively at the achievement of outcome-level goals that were specified at the project start and, conversely, that given distal goals could only be reached by pursuing the pre-specified proximal objectives (Thagard and Croft, 1999).

In sum, although in industrial R&D projects, operational goals are normally seen as instrumental steps toward the achievement of outcome-level goals, the link between the two levels may become uncertain. Hence, the actors concerned may become unsure about which goals to focus upon, and in the limit, they may focus on either level (Heslin and Wang, 2013), whether as a result of their behavioral limitations or of rational decisions.

2.1.3 Projects, problems, and knowledge sets

Each research project identifies a problem and defines, at least approximately, the means, knowledge, and methods by which the project goals should be attained (Lundin and Soderholm, 1995). Even leaving aside possible barriers to knowledge flows from the organizational and social fabric of projects, this purview of problems and approaches may engender a tendency for knowledge search to linger within the project itself, rather than to draw freely from all the projects within the organization.[2] Indeed, as each project addresses a distinct problem, each will identify a set of

[1] Psychological investigations of goal setting highlight the wisdom of that logic. "Setting proximal goals facilitates goal pursuit by increasing motivation, by developing higher self-efficacy, by better detection and management of errors, and by learning" (Sun and Frese, 2013, 185).

[2] In this study, the word "project," without further qualifications, will refer to a problem and the approaches to its solution that were originally envisioned. Instead, we will use the terms "project organization" and "project team" to refer to the activity system that is set in place for the solution of that problem and to the workgroup that is assigned to that activity system, respectively.

requisite knowledge that will be largely disjoint from the corresponding sets of other projects.[3] Therefore, project teams that are broadly matched to the knowledge set of their project will find the knowledge employed in other projects to be on average less familiar.

Moreover, even when essentially similar approaches can be used across different projects, their transfer from a different project may be difficult. Indeed, successful transfer of knowledge from a problem is limited by the ability of the recipients to notice the pertinence of that knowledge to the target problem (Gick and Holyoak, 1980; Holyoak, 2012). By implication, learning is the easiest when in a knowledge exchange interaction, it is possible to present, alongside the "solution," a one-to-one mapping between the concepts of the source problem and the destination problem—and it is obviously the easiest when the sender and receiver are tackling the same problem.

In sum, knowledge search that crosses a project's "epistemic" boundaries (i.e., boundaries of problems and envisioned knowledge sets) is typically more challenging than knowledge search that does not, either in terms of the type of knowledge that it seeks to access or in terms of how easy it is to appropriate that knowledge, or both. Therefore, in the context of project-based industrial R&D, we can meaningfully characterize intra-organizational individual knowledge search behavior in terms of whether it seeks scientific and technical advice about the knowledge and the problem of one's project or of other projects—in short, whether it seeks "intra-project" or "cross-project" advice.

It is to be noted that an asymmetry exists also within a project's knowledge set. The knowledge and methods that are available for the attainment of operational-level objectives are relatively reliable. Accordingly, those methods are likely to be rather exhaustively and prescriptively specified in the project's knowledge. In contrast, it is generally more debatable which knowledge and methods should be used for attaining outcome-level innovation goals (Dasgupta and David, 1994; Stephan, 1996). Therefore, some of the methods that will be eventually proven useful in that respect may not be initially envisioned as belonging to the project's knowledge set, but may have been envisioned by other projects. Across different R&D professionals, this asymmetry may create differential incentives to engage in cross-project search, depending on which goals receive the most of their attention—as the next section will elucidate.

Despite the importance of organizationally set goals, it is obvious that individual search decisions are influenced by other factors as well, notably, by the different opportunities for learning that alternative knowledge sourcing strategies can offer. However, we argue that in the context of industrial R&D, personal learning objectives are a factor of lesser importance for our investigation, since the performance of the research tasks itself offers plenty of learning opportunities (Stern, 2004) and since industrial R&D organizations seem to have means to effectively sanction research professionals who stray too far from the laboratory's purposes (Stephan, 1996).

2.2 Multiple goal pursuit and goal framing

People find trade-offs difficult to execute, so that when multiple goals compete, they are dealt with through processes of selective attention (Speekenbrink and Shanks, 2013). Goal framing theory proposes that an important way by which people simplify their decision situation is by "framing" it (Lindenberg, 1993, 2008)—one goal is pushed to the foreground of the decision maker's attention (making it "salient"), while other goals are left at the periphery of it—and that the goal that is salient influences the criteria for selecting and ordering the alternatives disproportionately more than the other goals (Lindenberg and Frey, 1993; Lindenberg, 2008). Industrial researchers are presented with distal and proximal goals by their organizations, and they are also likely to aim, to a lesser extent, at private learning benefits. Owing to such goal complexity, simplification of the situation through framing is to be expected.

As to what determines goal salience, the goals of research projects are assigned by the organization. Hence, the decision of researchers is one about their commitment to each goal (Heslin and

[3] Obviously, this admits of degree. In R&D organizations such as the one we investigate, which undertake a moderate number of long-term projects for the development of products characterized by significant novelty, each project is almost a "knowledge island of its own" (cf. Setting and method section). In contrast, in organizations that follow a replication strategy and operate relatively standardized templates across different projects, the degree of overlap between the knowledge sets of different projects may be substantial.

Wang, 2013). By using legitimate authority, the supervisor can get initial commitment (Locke, 1996). Then, commitment is enhanced or weakened by what the individuals think can be achieved (expectancy) and what they would like to achieve or think should be achieved (desirability) (Heslin and Wang, 2013; Klein *et al.*, 2013). Therefore, if the organization of work affects either of those determinants, it is likely to also influence goal salience and to orient search toward that knowledge that is regarded as most useful for pursuing the salient goal.

2.3 Job attributes and goal expectancy

Jobs pose demands on employees. However, research in organizational behavior emphasizes that it is the combined effect of job demands and employee abilities to meet those demands—rather than either of them in isolation—that is responsible for many work-related outcomes. Therefore, that research field has articulated the concept of person–job fit (Edwards, 1991) which captures the degree of alignment between the demands of the job and the abilities that the individual can draw from to meet those demands.[4,5]

In the context of industrial R&D, the demands that jobs pose, and the resources that jobs require, mainly arise from research projects. Moreover, both demands and resources are largely knowledge-related. Hence, we specify the construct as one of PTF to capture the extent to which a researcher's knowledge matches the knowledge domains of her assigned projects. Owing to the fit between their knowledge and the tasks that their projects assign to them, high-PTF R&D professionals are capable of successfully controlling and impacting circumstances and are likely to be confident about their chances of meeting their projects' goals. Conversely, low PTF characterizes R&D professionals whose knowledge and expertise are not so well-matched to their assigned tasks, leading them to anticipate that meeting their project's goals may be challenging.

PTF is at least partly a byproduct of managerial decisions. The assignment of staff to projects is not trivial matter, as it is subject to various constraints (e.g. staff availability) and can be guided by alternative criteria of assignment. Moreover, it requires precise managerial understanding about the knowledge and competencies demanded by the project and those possessed by eligible researchers. Consequently, it often results in an imperfect fit of the knowledge and competencies of individual researchers with those demanded by their projects.

2.4 Person–task fit and cross-project search

To develop theory about the influence of PTF on knowledge search by industrial researchers, we perform a thought experiment, considering three mutually exclusive ranges of the researchers' PTF: low, high, and moderate.

A low PTF means that the knowledge and methods that are considered standard for their assigned project are not adequately mastered. Therefore, reaching of project objectives by the individual worker will look uncertain. However, since outcome-level goals are more emergent, the failure to achieve them can be condoned, whereas organizations will not be as forgiving of failures to achieve proximal goals, for which more reliable knowledge is available (Dasgupta and David, 1994; Stephan, 1996). This should engender a keen awareness that proximal goals ought to be achieved (i.e. a strong sense of desirability), promoting those goals to become more salient relative to distal goals. For low-PTF researchers, an improvement of their understanding of the standard methods of their projects' knowledge domains offers the best chance of meeting their salient goals. Moreover, searching for those methods as already contextualized to their project

[4] A similar logic also underlies recent theories that originated in the Human Resource Management literature, such as the Job Demands–Resources (JD-R) model (Bakker and Demerouti, 2007; Kwon and Kim, 2020).

[5] Obviously, people may be poorly fit to their projects also for motivational reasons (e.g. if they have no interest in the project). However, it is important to note that this notion of fit is conceptually distinct from person–job fit. Both the OB literature and the JD-R model regard motivation as one of the *consequences* of the person–job fit (Edwards, 1991; Kwon and Kim, 2020), not as a dimension of it. Moreover, while motivation certainly impacts work engagement, we know of no study to have proposed a link between motivation and the locus of knowledge search. Furthermore, motivational issues do not seem to be severe in the kind of setting we were discussing ("shirking is rarely an issue in science" [Stephan, 1996: 1206]). For all these reasons, we chose not to make motivation a core component of our theoretical framework, although we indirectly controlled for it in our empirical study (cf. De Spiegelaere *et al.*, 2016).

make knowledge absorption easier. Therefore, it is to be expected that those researchers will tend to engage in intra-project knowledge search.

Conversely, high-PTF researchers master the standard methods of their projects and exceed the common level of competence in those methods. Therefore, those R&D professionals will perceive that by applying that knowledge, they can attain operational objectives without difficulty and that these can become steppingstones in their pursuit of novel solutions. Hence, high-PTF R&D professionals will have no reasons to weaken their initial commitment to outcome-level goals on account of low expectancy or of low desirability. Rather, organizational learning scholars have highlighted how competence can induce learners to leverage their extant skills more and more, achieving perhaps short-term benefits, but eventually becoming entrapped into the exploitation of existing competencies (March, 1991; Arts and Fleming, 2018). Moreover, competency traps can arise even as a result of structural features of rational decision-making (Denrell and Le Mens, 2020), making it plausible that competency traps also occur among R&D professionals who are fully committed to learning and innovation.

In the context of exploration that we are discussing, the choice would not be—trivially—between undertaking an activity one has tried many times and one that the individual is less proficient in. Rather, it is between pursuing innovation through a logic of *interrogation*, which relies on further intense scrutiny and examination of those knowledge domains that are typically regarded as most useful for a given class of problems (Kaplan and Vakili, 2015; Rhee and Leonardi, 2018), or through a logic of *recombination*, which seeks to integrate diverse information from different domains.

In this context, researchers with a high PTF are likely to perceive that cross-project knowledge search would be comparatively less fruitful, as it would require them to disperse cognitive effort across unfamiliar knowledge domains and knowledge applications, thus allowing for less intensive use of their expertise. Therefore, they would rather seek to produce good ideas by deepening (Katila and Ahuja, 2002) their understanding of their project's knowledge even further, as that would make it possible to identify anomalies specific to their domain (Kaplan and Vakili, 2015), to understand detail and nuances about existing local solutions and practices, and to innovate by bending or breaking those local solutions (Taylor and Greve, 2006). Moreover, possessing knowledge of considerable depth in a particular domain is known to make researchers very effective at eliminating fruitless paths of research in that domain (Fleming and Sorenson, 2004), relatively more so than if they stray from it. Therefore, the knowledge search of high-PTF researchers is comparatively more likely to focus on the typical domain knowledge, and on the typical problem of their project, though for reasons altogether different from those of low-PTF researchers.

Unlike both these groups of workers, researchers with an intermediate, moderate level of PTF would have an adequate mastery of the standard methods of their projects. For them, the performance of operational tasks should not pose as serious a challenge as to displace outcome-level goals of innovation. However, these workers are less deeply invested in the methods and problems of their projects than high-PTF ones. Hence, they would perceive that seeking advice about the knowledge and the problem of other projects would have a comparatively lower opportunity cost. Therefore, we expect that at moderate levels of PTF, a larger portion of a worker's knowledge exchanges will be used for seeking scientific and technical advice about other projects than at high and low levels of PTF. Hence,

> *Hypothesis*: *There is an inverted U-shaped relationship between the industrial researchers and scientists' person–task fit and the likelihood that they will seek cross-project scientific and technical advice through their interactions.*

3. Setting and method

3.1 Research setting: R&D projects in a pharmaceutical laboratory

We conducted our study at the corporate R&D center of a pharmaceutical company headquartered in Europe (henceforth Alpha) with subsidiaries across the globe. Alpha has a strong focus on in-house R&D: it is one of the top patent-filing companies in Europe, and 75% of its turnover is generated by its own R&D division. Our study focused on the chemistry, manufacturing, and control (CMC) unit within that division. The CMC unit is a project-based type of organization, where all development activities are organized in projects. While CMC also has permanent departments, "projects take priority and direct the day-to-day work of employees" (Head of Department). Those projects are highly specialized: "each project is a knowledge island of itself" (Head of CMC). For example, "while one project is working on inhaled corticosteroids another one is working on enzyme replacement therapies. These are two very distinct areas with specificities relating not just to the disease and the drug, but also to the delivery mechanisms" (Head of R&D).

Projects have a flat and flexible structure and are led by a project manager who is accountable for the entire development process. The projects conducted within CMC are usually at middle or late stages of the R&D process and entail a mix of basic and applied research, requiring a combination of basic knowledge (e.g. chemistry and biology), applied knowledge (e.g. pharmaceutics), and analytics (e.g. statistics and mathematical modelling). At the time we collected our data, CMC had 12 ongoing projects.

Our target population consisted of 128 people: 37 scientists, 48 laboratory technical staff, 10 heads of unit, 6 heads of department, 5 project managers, and 22 analytics staff. The process of assignment of staff to project is to a significant extent exogenous to the employee (Head of CMC). The R&D personnel in the company is quite stable—the average tenure in our sample is 10 years, and 60% of the employees spent more than 4 years in the company. In the short to medium term, the staff is virtually fixed, as the hiring of new personnel takes a significant amount of time and needs to be thoroughly justified to the higher levels of the organization. Therefore, when a project is set to start, it can select its staff only from a fixed pool of people. Research staff are assigned to projects according to priority and ability, but "project managers and heads of department bargain over personnel. The assignment to a project is also the result of this bargaining process" (Head of CMC). As a result, project managers may end up staffing their projects with employees who are not their preferred choice, which explains the cross-case variation in PTF we observed. In our sample, the modal number of projects that employees are assigned to is one (45% of cases), the average number is two, and the maximum number is six (one case).

3.2 Data sources

Our study adopts an "insider econometrics research design" (Obloj and Zenger, 2017), drawing on primary and secondary intrafirm data, supplemented by discussions with managers of Alpha. Specifically, we interviewed the Chief Executive Officer (CEO) and 14 other people within the company and the CMC unit, including the Director of R&D, the Head of CMC, the Human Resources Business Partner of the R&D, three project managers, three scientists and three technicians randomly selected from the CMC R&D population, one member of staff from the general administration office, and one company budget controller. Each interview lasted for about one and a half hours. Written notes were taken, and interview summaries were written after each interview.

We could also access archival data about the researchers' patent applications and research publications, their project formal membership, department affiliation, rank, tenure, age, gender, and academic background, as well as documents related to CMC's strategy and organizational structure and the minutes of some meetings between the management and R&D professionals.

The purpose of the qualitative part of the research was to act as a preparation for and a supplement to the quantitative analyses on which the study is based. Nevertheless, the qualitative investigation was crucial to understand more precisely the innovation process of the company, the formal mechanisms and procedure of CMC's R&D project management, and the culture of the company. Moreover, it left us satisfied that the measures we performed through the questionnaire were correctly understood by the respondents and that they were related to phenomena that were relevant to them. Given the sensitivity of some information, the research team had to sign a non-disclosure agreement with the company.

As to the quantitative evidence, we use an electronically delivered questionnaire to perform a sociometric survey about friendship contacts, professional advice contacts, and contacts for the acquisition of scientific and technical advice within the laboratory. Moreover, we also asked questions related to each researcher's own assessment of their PTF. The questionnaire was delivered to the entire population of CMC researchers over 4weeks, with reminders sent in week 2 and week 3. Eventually, we obtained usable data for 766 project-specific knowledge acquisition interactions among 93 researchers (response rate: 82%).[6]

3.3 Method

Our main empirical objective is to link different levels of PTF to individual choices about cross-project vs. intra-project scientific and technical advice, while controlling for relevant confounding factors. At the individual level, these choices can be described by the proportion of cross-project advice (0,1) in the total number of reported scientific and technical advice acquisitions. Accordingly, we tested the quadratic (∩-shaped) relationship between individual *i*'s PTF and the proportion of cross-project acquisitions of the same individual, estimating the following equation:

$$\text{Proportion cross} - \text{project acquisitions} = \alpha + \beta_1 \text{PTF} + \beta_2 \text{PTF}^2 + \delta x + \omega z + \varepsilon, \qquad (1)$$

In equation (1), x refers to individual attributes, and z to project dummies. Following an established strategy for fractional dependent variables, we estimated a generalized linear model with a logit link function, assuming a Bernoulli family distribution, and we calculated robust standard errors.

Since dyadic attributes are also likely to be implicated in the processes that underlie advice transactions between people, we complemented the individual-level analysis with an advice acquisition–level analysis (Kleinbaum, 2012). In the latter, we tested the quadratic relationship between *i*'s PTF and the probability that an advice acquisition from individual *j* is cross-project. Using a logit regression model with robust standard errors, two-way clustered for both *i* and *j*, we estimated variants of the following equation:

$$P(Y) = \Phi\left(\alpha + \beta_1 \text{PPF}_i + \beta_2 \text{PPF}_i^2 + \delta_1 x_{ij} + \delta_2 x_i + \delta_3 x_j + \omega z + \varepsilon_i + \varepsilon_j\right), \qquad (2)$$

where Y takes a value of 1 if the advice is cross-project, Φ is a logistic cumulative distribution function, x_{ij} corresponds to dyadic-level attributes, x_i and x_j indicate individual level attributes, and z refers to project dummies.

3.4 Measures

3.4.1 Cross-project scientific and technical advice

In the sociometric survey, each respondent was asked to specify each project for which they considered to be involved in knowledge-based interactions and then select from a dynamic list of all employees the names of her or his scientific knowledge contacts for each specific project. More precisely, they were instructed to "*Select the people from whom you most frequently obtain knowledge related to the scientific aspects of this project.*" With this information, we could identify a knowledge acquisition reported by employee *i* with employee *j* related to project p_n, where $n = 1, \ldots, 12$. Using the archival information provided by the company, we classified each one of these exchanges as cross-project or intra-project: if *i* reported an exchange with *j* for project p_n, and p_n was not part of the set of projects in which *i* had a formal membership, then this variable takes a value of 1, and 0 if *i* was a formal member of p_n.

3.4.2 PTF

To operationalize PTF, we developed three items along the lines of similar items used in the PPatVal-EU survey of inventors (cf. Giuri *et al.*, 2007): 1. "My prior experience combines well with the firm's capabilities in the accomplishment of the projects to which I am assigned"; 2. "My prior inventive experience can be readily applied to the projects to which I am assigned"; and 3. "My technical expertise allows me to easily carry out the projects to which I am assigned." The first statement captures the idea of complementarity between a worker's human capital and

[6] *t*-tests revealed no statistically significant differences between respondents and non-respondents in terms of age, gender, tenure, level of education, number of previous patents applications, and number of previous scientific publications.

the capabilities of the firm, relative to specific projects. The other two statements focus on the applicability of prior inventive experience, and of technical expertise, to the assigned projects. The answers were collected on a seven-point Likert scale (Cronbach's alpha: 0.88).

3.4.3 Control variables

We controlled for several elements that might confound the hypothesized relationship. At the individual level, we used dummy variables to identify distinct formal roles (e.g. Head of Department, Project Manager, Scientist, etc.), to control for the possibility that these might also create different opportunities and motivations to search for knowledge of a specific kind. We controlled for gender and for the level of education, since individuals with a doctoral degree can be expected to be especially skilled in recombining knowledge (Gruber *et al.*, 2013). We controlled for network constraint in the organizational non-project advice network, as certain structural positions in the R&D professionals' informal networks can provide more opportunities for identifying different sources of knowledge (Burt, 2004). To account for human capital-based explanations, we included controls for the number of patent applications and of papers published in academic journals by each respondent. We also included a control for the tenure within the company to account for advantages it might create in the identification of knowledge sources and firm-specific human capital. Finally, we controlled for confounding effects that might owe to the formal organizational structure. Specifically, we added department-level and project-level dummies. Furthermore, we controlled for the degree of autonomy that researchers have in their projects as autonomy influences the motivation and behavior of researchers (Gambardella *et al.*, 2020). Specifically, we asked respondents to indicate to what extent 1. "I have considerable freedom in determining my tasks"; 2. "I can decide how to allocate my work-time among different tasks"; and 3. "I can freely decide how to do my tasks."

At the knowledge acquisition level, we also controlled for multiplexity, homophily, propinquity, informal structural positions, and disposition (Dahlander and McFarland, 2013). Since extant research identified friendship and (non-scientific) advice ties as relevant dimensions of the informal organization (Gibbons, 2004), we controlled for friendship and non-project advice relationships between i and j, as well as for their non-project advice network constraint and their boundary spanning through the E–I index. We obtained this information through the sociometric survey. We also used dummies indicating whether i and j belonged to the same department; dummies indicating whether they belonged to the same projects, to account for propinquity; and a dummy for same gender, to account for homophily. We also included controls for organizational rank and role to account for rank-based motivations: j project manager and j head of department. Finally, to control for any unobservable heterogeneity across projects (e.g. budgets, equipment, collegiality, and leadership style), we included project dummies indicating the project affiliation of i.

4. Results

Tables 1 and 2 report summary statistics and correlation coefficients for individual- and knowledge acquisition–level data, respectively.

4.1 Individual level

Table 3 reports the regression results related to the proportion of cross-project acquisitions. Model (1) is the base model, only containing the control variables. Models (2) and (3) introduce the linear and quadratic measures of PTF, respectively. We observe an inverted U-shaped relationship.

We tested whether the sign of the slope of the curve shifted according to expectations (Haans *et al.*, 2016). We could not reject the presence of an inverted U-shape effect ($P < 0.04$, t-value = 1.77), with the extreme point of the curve at a 4.39 value of PTF and a 95% Fieller interval of [0.41, 5.20]. Figure 1 plots the estimated marginal effects of PTF, which are consistent with the expected shape.

Table 1. Descriptive statistics

Variable	Observed	Mean	Std. Dev.	Minimum	Maximum
Descriptive statistics at the individual level					
% cross-project ST advice	93	0.336	0.379	0	1
PTF	93	5.011	1.248	2.333	7
PTF squared	93	26.648	11.854	5.444	49
Autonomy	93	4.821	1.369	1.667	7
Patent applications	93	3.153	9.707	0	67
Publications	93	1.143	0.2.806	0	17
Female	93	0.622	0.487	0	1
Scientist	93	0.306	0.463	0	1
Technician	93	0.387	0.49	0	1
Project manager	93	0.041	0.199	0	1
Head of department	93	0.041	0.199	0	1
Head of unit	93	0.097	0.30	0	1
Analyst[a]	93	0.129	0.34	0	1
PhD	93	0.061	0.241	0	1
Tenure (years)	93	9.948	9.306	0.167	34.083
Network constraint	93	0.442	0.263	0.08	1
Descriptive statistics at the ST advice acquisition level					
Cross-project ST advice	766	0.288	0.453	0	1
PTF	766	4.965	1.348	2.333	7
PTF squared	766	26.462	12.487	5.444	49
Autonomy	766	5.07	1.324	1.667	7
Same gender	766	0.572	0.495	0	1
Same department	766	0.643	0.48	0	1
Number of projects	766	2.128	1.21	0	6
Head of department	766	0.06	0.237	0	1
Project manager j	766	0.041	0.197	0	1
Scientist j	766	0.499	0.5	0	1
Non-project advice tie	766	0.255	0.436	0	1
Friendship tie	766	0.221	0.415	0	1
Network constraint i	766	0.413	0.239	0.08	1
Network constraint j	766	0.343	0.2	0.08	1
E–I index i	766	−0.214	0.531	−1	1
E–I index j	766	−0.246	0.459	−1	1

[a]This has been used as the baseline category in estimations; ST: scientific and technological.

Even though assignment into projects (and, therefore, PTF) is not under the control of researchers, it cannot be assumed to be completely exogenous to the outcome of interest. For example, there is a possibility that any given individual may be at a higher risk of assignment into better fitting projects due to individual characteristics or strategic behaviors. In principle, this could engender reverse causality, a source of endogeneity. Although we could count on a relatively rich dataset that allowed us to control for manifold factors, due to the cross-sectional nature of our data, endogeneity cannot be ruled out in principle, and we were unable to find a suitable instrument (i.e., strong and exogenous) to address this concern with instrumental variables estimation. Therefore, we resorted to the Gaussian Copula control function method (Park and Gupta, 2012). Our endogenous regressor is continuous and non-normally distributed (Shapiro–Wilk test, $P = 0.005$), and the error term approximates a normal distribution—thereby meeting the assumptions of the method. Hence, we calculated the Gaussian Copula control and included it in model 4. Its coefficient is not significant (indicating the insignificant presence of endogeneity), and the coefficients of interest (PTF and PTF squared) remain essentially the same as in model 3. These results also assuage doubts that other omitted variables (say, status and ability levels, above and beyond what could be captured by the number of publications, patent applications, and organizational ranks) may have confounded our results.

Table 2. Bivariate correlations

Pairwise Correlations at the individual level

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. % cross-project ST advice	1.000													
2. PTF	−0.018	1.000												
3. Autonomy	0.070	0.389	1.000											
4. Patent applications	0.019	0.106	0.021	1.000										
5. Publications	−0.139	−0.007	−0.143	0.059	1.000									
6. Female	0.009	−0.076	0.060	−0.125	−0.180	1.000								
7. Scientist	−0.123	0.039	0.144	−0.057	0.267	−0.108	1.000							
8. Technician	−0.134	−0.209	−0.182	−0.283	−0.176	−0.067	−0.535	1.000						
9. Project manager	−0.184	0.086	−0.051	0.308	−0.046	−0.020	−0.129	−0.169	1.000					
10. Head of department	0.204	−0.042	0.074	0.452	−0.051	−0.069	−0.141	−0.145	−0.045	1.000				
11. Head of unit	0.211	0.310	0.150	0.177	0.033	−0.121	−0.22	−0.260	−0.07	−0.06	1.000			
12. PhD	0.011	−0.007	−0.002	−0.075	0.036	0.105	0.150	−0.029	−0.048	−0.053	−0.090	1.000		
13. Tenure (years)	0.037	0.064	−0.067	0.189	−0.011	−0.008	−0.228	0.023	0.009	0.203	−0.202	−0.236	1.000	
14. Network constraint	0.047	−0.315	−0.199	−0.230	−0.168	0.213	−0.237	0.157	−0.010	−0.150	−0.015	−0.055	0.080	1.000

Pairwise correlations at the ST advice-acquisition level

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
1. Cross-project ST advice	1.000														
2. PTF	0.165	1.000													
3. Autonomy	0.160	0.414	1.000												
4. Same gender	0.052	−0.017	−0.065	1.000											
5. Same department	0.234	−0.008	−0.116	0.033	1.000										
6. Number of projects *i*	−0.239	−0.209	0.063	−0.006	−0.142	1.000									
7. Head of department *j*	−0.018	0.015	−0.019	0.023	−0.025	−0.062	1.000								
8 Project manager *j*	−0.046	0.002	−0.074	0.061	−0.235	−0.001	−0.052	1.000							
9. Scientist *j*	0.037	0.011	0.083	−0.057	−0.006	0.035	−0.251	−0.205	1.000						
10. Non-project advice tie	0.027	0.049	0.054	0.054	0.169	−0.047	0.160	−0.046	−0.072	1.000					
11. Friendship tie	0.020	0.083	−0.023	0.102	0.224	0.012	−0.108	0.030	−0.024	0.180	1.000				
12. Network constraint *i*	0.042	−0.287	−0.208	0.114	0.051	0.119	0.040	0.073	−0.094	−0.256	−0.064	1.000			
13. Network constraint *j*	−0.037	−0.021	0.009	0.086	0.009	0.085	−0.135	−0.021	−0.213	−0.080	0.072	0.022	1.000		
14. E–I index *i*	−0.108	−0.149	0.104	0.037	−0.392	0.209	0.014	0.030	−0.083	−0.130	−0.146	0.033	0.130	1.000	
15. E–I index *j*	0.003	−0.106	−0.012	0.086	−0.207	0.041	0.190	0.181	0.005	−0.035	−0.146	0.169	−0.021	0.211	1.000

Abbreviation: ST, scientific and technological.

Table 3. Generalized Linear Model (GLM) estimations of the percentage of cross-project ST advice

Variables	Model 1	Model 2	Model 3	Model 4
Patent applications	0.166	0.137	0.134	0.00780
	(0.126)	(0.132)	(0.141)	(0.165)
Publications	0.198**	0.194**	0.238**	0.177*
	(0.0877)	(0.0914)	(0.0951)	(0.0980)
Autonomy	0.0774	0.155	0.189	0.101
	(0.190)	(0.194)	(0.195)	(0.203)
Female	−0.776	−0.886	−0.826	−0.946*
	(0.530)	(0.558)	(0.560)	(0.552)
Scientist	−4.263*	−4.169*	−4.624*	−1.324*
	(2.218)	(2.233)	(2.383)	(0.752)
Technician	−3.404*	−3.345*	−3.879*	−1.140
	(1.880)	(1.893)	(2.063)	(0.695)
Project manager	11.57***	11.70***	12.19***	15.97***
	(3.022)	(3.047)	(3.508)	(2.869)
Head of department	26.24***	25.80***	24.11***	29.39***
	(2.542)	(2.522)	(2.890)	(1.457)
Head of unit	−4.032*	−3.814	−4.179	−4.240
	(2.339)	(2.350)	(2.571)	(2.6513)
PhD	−0.676	−0.624	−1.226	−0.294
	(1.175)	(1.211)	(1.232)	(1.155)
Tenure (years)	0.0401	0.0448	0.0326	0.0335
	(0.0300)	(0.0328)	(0.0310)	(0.0321)
Advice network constraint	−0.910	−1.253	−0.954	0.0807
	(1.215)	(1.373)	(1.300)	(1.126)
PTF		−0.172	2.547**	2.215**
		(0.219)	(1.268)	(1.081)
PTF squared			−0.290**	−0.268**
			(0.130)	(0.120)
Gaussian copula control				0.0676
				(1.212)
Constant	6.990***	7.540***	2.126	−0.170
	(2.626)	(2.870)	(3.483)	(5.007)
Log pseudolikelihood	−28.6397	−28.5297	−29.0207	−28.5018
Project and department dummies	Yes	Yes	Yes	Yes
Observations	93	93	93	93

Two-tailed tests. Robust standard errors are in parentheses
*** $P < 0.01$,
** $P < 0.05$,
* $P < 0.1$.
Abbreviation: ST, scientific and technological.

4.2 Advice acquisition level

Table 4 contains regression results on the probability of a cross-project scientific and technical advice acquisition. The models parallel those in Table 3. All the focal coefficients are individually significant at the 0.05 (or more stringent) level. We also tested whether the sign of the slope of the curves shifted according to the expected relationships and found strongly consistent results. In Figure 1, we plotted the estimated marginal effects of the focal predictor. As predicted, we observe an inverted U-shaped relationship for PTF ($P < 0.009$, t-value $= 2.36$), with an extreme point at 4.73 and a 95% Fieller interval of [3.66, 5.18].

Among the ancillary findings from these analyses, we notice a significant effect of autonomy ($\beta = 0.588$, $P < 0.01$). This squares with the common wisdom that researchers are largely driven by scientific curiosity and intellectual challenges (e.g. Stephan, 1996). Therefore, provided that they are given sufficient leeway, they direct themselves more often toward exploring less familiar methods and problems, rather than toward further enquiry of more familiar ones. A second ancillary finding is the large and significant coefficient of same department ($\beta = 1.229$, $P < 0.01$).

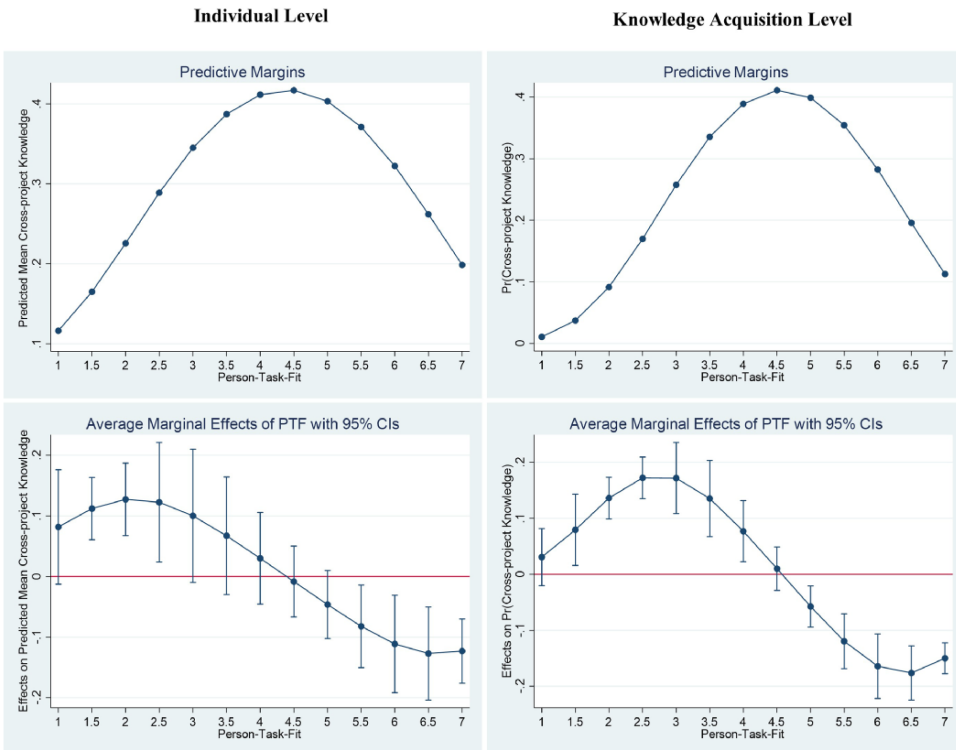

Figure 1. Marginal effects of PTF on cross-project knowledge acquisition

It is well known that the professionals within R&D organizations rely heavily on social sources of knowledge in their immediate vicinity, typically within the same department. Our finding suggests that in project-based organizations, in which the members of a given department have opportunities to participate in various projects, people located in the proximity of the focal actor also become important conduits of cross-project scientific and technical advice toward that actor.

4.3 Robustness checks

We ran a series of robustness analyses to validate our results, including among others, sample selection bias and U-shaped confirmation tests. These analyses are available in the online Appendix.

4.4 Mechanism validation

Although our survey data do not allow for a complete direct observation of the postulated mechanism, from interviews of a few members of Alpha's management team, we gathered qualitative evidence that directly supports several of the links in the causal chain we posit. This evidence is presented in the online Appendix.

5. Discussion

For science-intensive firms endowed with a large knowledge base with potential for recombination, focusing on the exploitation of internal knowledge can be an effective innovation strategy. To exploit their internal knowledge, firms can rely on their networks of researchers through which they can procure the exchange of different types of knowledge and perspectives, thus increasing the likelihood of recombination. Because innovation outcomes benefit from search

Table 4. Logit estimations of the probability of a cross-project ST advice acquisition

Variables	Model 1	Model 2	Model 3
Autonomy *i*	0.513**	0.453**	0.588***
	(0.202)	(0.181)	(0.183)
Same gender	0.220	0.108	0.287
	(0.287)	(0.280)	(0.286)
Same department	1.293***	1.303***	1.229***
	(0.337)	(0.354)	(0.355)
Number of projects *i*	−0.637***	−0.558***	−0.647***
	(0.230)	(0.202)	(0.211)
Head of department *j*	−0.836**	−1.154***	−1.090**
	(0.415)	(0.441)	(0.536)
Project manager *j*	0.155	−0.440	−0.607
	(0.503)	(0.522)	(0.545)
Scientist *j*	−0.0536	−0.150	−0.245
	(0.256)	(0.256)	(0.261)
Non-project advice tie	0.140	0.151	0.0670
	(0.282)	(0.276)	(0.283)
Friendship tie	−0.335	−0.477	−0.470*
	(0.280)	(0.300)	(0.275)
PTF		−0.0889	4.400**
		(0.204)	(1.957)
PTF squared			−0.481**
		(0.201)	
Constant	−2.369	−1.388	−11.78**
	(2.572)	(3.013)	(5.762)
Pseudo R^2	0.2808	0.3198	0.3560
χ^2	242.53	261.89	223.81
Project dummies	Yes	Yes	Yes
Network controls	Yes	Yes	Yes
Observations	766	766	766

Two-tailed tests. Robust standard errors are in parentheses.
Two-way error clustering: ST: scientific and technological.
***$P < 0.01$,
**$P < 0.05$,
*$P < 0.1$.
Abbreviation: ST, scientific and technological.

breadth (Dahlander *et al.*, 2016), it is in the interest of R&D organizations that their scientific staff supplement their projects with knowledge and perspectives from other projects as well.

We have posited that industrial R&D professionals, driven by their perceptions of their odds of failure in operational tasks and of attainment of innovation goals, and by their prior learning, will have a greater or lesser propensity to seek cross-project scientific and technical project–related advice through their informal interactions. Our core argument is that differences in individual PTF can lead R&D professionals to frame their situation differently, causing some goals to become salient and others to be pushed to the background of the researchers' cognition (Lindenberg and Foss, 2011), thus influencing the researchers' knowledge search patterns. Specifically, we have argued, and found supporting evidence about, that PTF—a job attribute that managers can directly influence through their project staffing decisions—has a non-linear, inverted U-shaped effect on the quest for cross-project scientific and technical advice.

Our study makes multiple theoretical contributions most specifically to research on individual search and to research on the management and organization of R&D. First, we contribute an explanation of knowledge search that is placed in a middle ground between structural determinism theories and rational choice theories. Several studies highlight that search is shaped by organization structural variables (e.g. Argyres and Silverman, 2004; Arora *et al.*, 2014). Others assume that search behavior is based on subjective individual weighting of costs and benefits (Nerkar and Paruchuri, 2005). Yet, others developed explanations based on both individual agency and organizational design (Brennecke *et al.*, 2021). Our explanation assumes intendedly rational individual decisions, though boundedly so. Specifically, by emphasizing the role of goal framing, we highlight the importance of attention processes. Research on individual decision-making has demonstrated that selective attention to goals can influence how a decision is made and the outcome of the process (Speekenbrink and Shanks, 2013). The empirical relevance of selective attention to goals has also been confirmed by qualitative research on individuals who pursue very long-term goals in knowledge-based organizations, in fields such as biomedical science and nanotechnologies (Bateman and Barry, 2012). The assumption that organizations cannot attend to all their goals simultaneously underlies the behavioral theory of the firm (Cyert and March, 1963), and classic studies of organizational decision-making have developed models for both individual (March and Shapira, 1992) and organizational (e.g. Vissa *et al.*, 2010) decision makers who are based on shifts of the focus of attention across alternative aspirations. Overall, our study connects concepts scattered across disciplines and fields and brings them to bear on individual knowledge search. In the process, we also introduce an incremental innovation to behavioral theories of attention allocation, where attention is conceived mainly as a trigger of search (March, 1988). By considering multiple partially conflicting goals, and by characterizing them as differing in terms of generality, we argue that attention allocation can also affect *what* is searched, once a knowledge search process has been triggered.

Second, we contribute to a nascent stream of research on the interaction between managerial and organization design decisions and informal networks and, more generally, to research on the organization of R&D (Argyres, 2018). Specifically, we highlight the importance of the organization of work and its impacts on job attributes. The model we develop, which focuses on the construct of PTF, fits with the logic of mainstream theories of organizational behavior, according to which employee attitudes and behaviors are shaped by resources set against job demands, as perceived in the work environment (Edwards, 1991; Bakker and Demerouti, 2007). While that logic has traditionally been applied to predicting major organizational outcomes such as job motivation and strain and, more recently, innovative behavior (Kwon and Kim, 2020), we show how casting that logic in a behavioral framework can also help predict more specific outcomes, such as the direction of search. In comparison with the research on the organization design of R&D, which has mostly focused on the effects of centralization (Argyres *et al.*, 2020) and organization structural features (Brennecke *et al.*, 2021), we draw the attention to the importance of the management and organization of work. This aligns with the interests of recent studies (Gambardella *et al.*, 2020), but we bring to bear such a focus on the study on knowledge search behavior. Given how important individual search is for knowledge transfer and invention (Maggitti *et al.*, 2013; Dahlander *et al.*, 2016), and the fact that search is often left to the individuals' discretion (Bailyn, 1985; Argyres *et al.*, 2020), we argue that jobs design should feature more prominently in this literature, as jobs constitute the most immediate environment of individual decisions. Therefore, we envision opportunities to investigate the relationship between PTF and job attributes on the one hand, and other dimensions of knowledge search, as well as search across organizational boundaries Finally, the main mechanisms that we invoke to explain the link between PTF and knowledge search patterns—goal parsing and goal framing—resonate with recent reflections in the organization design literature, which envisions a greater role for goal coordination and a reduced one for authority and reporting lines, in contemporary organizational design settings (Raveendran *et al.*, 2020).

Our study also has implications for the management of R&D. By demonstrating a relationship between knowledge search across projects with project–task fit, we offer evidence on how managerial choices can influence knowledge search. Specifically, R&D managers who aim to promote knowledge transfer across projects may want to staff their projects also with some researchers who are less than ideally matched to the project in terms of abilities and technical expertise. On the other hand, R&D managers need to know that staffing the project with people with large ability gaps (perhaps, in the hope of accelerating their professional development) may increase knowledge exchange conformity and delay knowledge diffusions across projects, besides hindering task performance.

This study also has limitations. First, R&D professionals' decisions to use informal interactions to search for cross-project or intra-project scientific and technical advice may reflect individual unobservable factors that we cannot fully account for in our analyses. Nonetheless, considering extant literature on scientists' motives and the nature of R&D activities, as well as what we gathered from interviews, our model complements the empirical analysis by proposing a causal interpretation for our results. Second, given our relatively small sample, the robustness checks we can perform at the individual level are limited. However, our individual-level analyses mirror our robust knowledge acquisition-level analyses, which inspire additional confidence in our findings. Finally, we have tested our theory using original, intra-organizational data from a firm's internal records and a survey of R&D professionals. Although such data sources may better capture tacit knowledge exchanges than patent data (Paruchuri and Awate, 2017), large-sample quantitative evidence can only provide limited insight into the actual mechanisms Therefore, it is a task for future qualitative research to develop a more fine-grained understanding into how organizational arrangements affect goal framing by R&D professionals.

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