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HOW DOES R&D WORKER RECRUITMENT AFFECT TECHNOLOGICAL EXPLORATION? A LONGITUDINAL STUDY OF R&D ACTIVE FIRMS IN DENMARK

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ABSTRACT. Little is known how hiring processes affect organizational learning over time. Drawing on the learning-by-hiring and absorptive capacity literature this paper argues that the recruitment of R&D workers influences the firm?s ability to perform exploratory search. The educational background of new R&D hires is used to determine their cognitive position in comparison to the firm. We expect that with increasing cognitive distance of new R&D hires, the novelty value of their knowledge increases, but the firm?s absorptive capacity decreases. Consequently, we contend that increasing cognitive distance between new R&D hires, and R&D workers already present in the firm, has a curvilinear effect on exploratory innovation. In addition to this, we expect that the relationship between cognitive distance and exploratory innovation is moderated by a firm?s employee diversity at the moment of hiring. Combining employer-employee matched panel data from Statistics Denmark in combination with patent application data from the European Patent Office we investigate the patenting behavior of 249 firms in the period of 1999-2004. While we find no effect of employee diversity, tentative results suggest there is a curvilinear effect of cognitive distance t-2 on exploratory innovation.

Jelcodes:O32,C33

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Abstract

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Keywords: labor mobility, cognitive distance, exploratory innovation, learning-by-hiring, patent

JEL Classification Codes: O32, C33

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1. INTRODUCTION

How do firms search for new technologies in the technological landscape? Theory on organizational learning and recombinatory search contends that firms are highly path-dependent in their innovative capabilities as a result of prior experience and knowledge (Levinthal & March, 1993; Levitt & March, 1988; March, 1991; Nelson & Winter, 1982). Consequently, the internal technological capabilities of a firm do not always suffice in achieving innovation and technological development through knowledge recombination. External knowledge sources provide an important way through which firms access new resources and allow firms to explore new technologies (Dyer & Singh, 1998; Rosenkopf & Almeida, 2003). Exploratory efforts are performed to pursuit new knowledge and entails a conscious shift away from the existing knowledge base of the firm (Lavie, Stettner, & Tushman, 2010; Levinthal & March, 1993; March, 1991). Exploratory innovation can be spurred through different external mechanisms (Almeida & Kogut, 1999; Jansen, Van Den Bosch, & Volberda, 2006; March, 1991) such as alliance formation (Mowery, Oxley, & Silverman, 1996; Rosenkopf & Almeida, 2003), licensing (Laursen, Leone, & Torrisi, 2010) and recruitment of personnel (Baty, Evan, & Rothermel, 1971; Pfeffer & Leblebici, 1973; Singh & Agrawal, 2011).

Recently so-called learning-by-hiring practices has received increasing attention, pointing to intentional hiring of highly-skilled employees by firms as a way to access new knowledge and skills (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song, Almeida, & Wu, 2003; Tzabbar, 2009). Such studies do not only consider mobility of skilled employees as a way of knowledge diffusion between firms, they also propose that hiring firms can explore new technologies and develop technological capabilities through access to the knowledge and skills of new recruits. To illustrate this, Song et al. (2003) show that inter-firm knowledge transfer as a result of inventor mobility is more likely to happen when a recruited inventor possesses distant technological knowledge from the hiring firm. More recently, Tzabbar (2009) finds that recruitment of technologically distant scientists results in significant technological repositioning of the firms involved.

The origins of exploratory search efforts of firms are far from established (Phelps, 2010). Yet, understanding these origins will allow us to understand how firms balance between exploitative and exploratory behavior (Lavie & Rosenkopf, 2006). Such understanding is important, because firms tend to pursue exploitative innovations at the expense of exploratory efforts. Firms do so, because exploitation produces higher short-term average returns and the process is more certain than exploration. However, exploration ensures a firm's adaptability and ultimately its survival (Levinthal & March, 1993). Recruitment of workers may bring different knowledge and skills into a hiring firm, which may draw upon these and explore new technological trajectories (Nelson & Winter, 1982). In order to understand how firms maintain a balance between exploration and exploitation this study specifically examines the recruitment of highly skilled research and development (R&D) workers.

To our knowledge, prior research has not yet addressed how recruitment of highly-skilled individuals affects the degree of exploratory search behavior of a firm, with Lacetera et al. (2004) and Tzabbar (2009) being the exception. Tzabbar (2009) however focuses solely on the effect of distant scientists (i.e. scientists that embody knowledge that is distant from the firms' knowledge base) on technological repositioning (i.e. significant exploratory behavior). And Lacetera et al. (2004) analyze the effect of star scientists on the adoption of science-based drug discovery (i.e. changing capabilities). This study instead focuses on recruitment of all Danish R&D workers taking the knowledge base of the new workers and hiring firm into account. We hypothesize that the cognitive distance between recruited R&D workers and the hiring firm has an inverted U-shaped relationship with the subsequent degree of exploratory search.

In addition to this, this study deals with three main limitations evident in the literature. First, the learning-by-hiring literature commonly depends on patent data (e.g.: Song et al., 2003; Tzabbar, 2009). Notwithstanding the rich information that patents contain, patent data has limited suitability for identification of recruitment. In order to identify instances of recruitment, highly skilled individuals should patent (sufficiently) during their employment. Hence, studies that utilize patent data to identify instances of recruitment use samples that represent a subset of all recruited R&D workers (Tzabbar, 2009). As a consequence, their limited recruitment measures may lead to an upward bias in the estimation of recruitment on exploratory behavior. We instead measure mobility of the whole population of Danish R&D workers.
Related to the previous limitation, the literature on learning-by-hiring has mainly focused on firm-to-firm mobility (Song et al., 2003; Tzabbar, 2009). In contrast, we also include R&D workers hired directly from university. This group of R&D workers may be most important for exploratory innovation as they are likely to bring in recent state of the art research from academia into the hiring firm (Herrera, Muñoz-Doyague, & Nieto, 2010; Lacetera et al., 2004; Zucker & Darby, 1996). In line with this argument, Ejsing, Kaiser, and Kongsted (2011) show that R&D workers from university (i.e. having worked at university after graduation) have the highest impact on patent output of the hiring firm.
A third limitation in the learning-by-hiring literature is that contingencies have not yet been fully explored (Tzabbar, 2009). That is, the effect of recruitment on exploration may be contingent upon internal mechanisms and characteristics of firms. To illustrate this point, Tzabbar (2009) shows that power asymmetries among scientists and the breadth of a firm's knowledge moderate the effect of distant scientist recruitment on technological repositioning. Drawing on the absorptive capacity and diversity literature, we expect that diversity in employee background already present in the firm, will affect the firm's receptiveness and use of newly recruited workers. Hence, we examine to what extent the relationship between R&D worker recruitment and exploratory innovation is contingent upon employee diversity within the hiring firm.

In this study we aim to address aforementioned limitations and contribute to the learning-by-hiring literature. In order to do so, we examine the effect of R&D recruitment on the degree of exploratory search at the firm-level. We follow prior research by characterizing exploratory innovation as a manifestation of exploratory search processes of the firm (Benner & Tushman, 2002; Phelps, 2010; Rosenkopf & Nerkar, 2001). We utilize a comprehensive dataset that combines R&D active firms in Denmark, their patents and mobility of R&D workers with a technical or scientific degree. The research question is formulated as follows:

How does the cognitive distance between recruited R&D workers and hiring firm affect the degree of exploratory search performed by the hiring firm and how does employee diversity at the hiring firm moderate this relationship?

The structure of this paper is as follows. In the next section we discuss relevant theories and derive hypotheses. Subsequently, the methods section describes our data, sample and variables used in this study. Section 4 discusses the preliminary results, and is followed by a short discussion and conclusion in section 5. The final section provides an outlook for further improvements of the paper.

2. THEORY AND HYPOTHESES

We draw on theories that serve as basis to understand how R&D worker recruitment affects exploratory search of hiring firms. Our theoretical framework builds on search theory and organizational learning (March, 1991), theory on absorptive capacity (Cohen & Levinthal, 1990), and we draw on the cognitive distance literature (Nooteboom, 2000). To spur innovative activity firms search for new inventions. Inventions are the result of combining knowledge components in a novel manner (Fleming, 2001; Fleming & Sorenson, 2001; Schumpeter, 1934). When an invention is commercialized we denote this as an innovation (Schumpeter, 1934). Search is an uncertain process which is affected by bounded rationality and the experience of prior accumulated knowledge (Fleming, 2001; Fleming & Sorenson, 2004). March (1991) distinguishes two types of search. Local search or exploitation is captured by terms like refinement, efficiency and selection (March, 1991: 71), and builds upon the knowledge, skills and structures already present in the firm (Jansen et al., 2006). This type of search creates knowledge which is close to the current knowledge base of the firm (Stuart & Podolny, 1996). As a result, exploitative innovations are typical incremental innovations and provide short-term benefits to the firm, due to its reliability and low search costs (Laursen, forthcoming; Lavie et al., 2010; Rosenkopf & Almeida, 2003). In contrast, distant or exploratory search refers to processes such as variation, experimentation and discovery (March 1991: 71). Exploratory firm behavior involves a "conscious effort to move away from current organizational routines and knowledge bases" (Katila and Ahuja 2002: 1184). Consequently, exploratory search creates new knowledge as a result of a novel recombination of different knowledge parts (Schumpeter, 1934). However, exploratory search involves uncertainty and relatively high costs, which naturally limits the firms' willingness to engage in exploratory activities (Levinthal & March, 1993; March, 1991). Yet, in order to remain innovative, firms need to conduct exploratory search which enables firms to survive in the long run (Levinthal & March, 1993; Phelps, 2010). We view exploration and exploitation as two ends of a continuum rather than two different and orthogonal aspects (Gupta, Smith, & Shalley, 2006). We do so, because the degree of relatedness of knowledge between the firm's knowledge base and the new knowledge obtained, points to the degree of exploration (Lavie et al., 2010). This is also consistent with the idea that dominant search behavior of firms changes over time from exploitative to exploratory and vice versa. In short, while an exploitative innovation builds upon the skills and knowledge already present in the firm, an exploratory innovation refers to "the creation of technological knowledge that is novel relative to a firm's extant knowledge stock" (Phelps, 2010: 892).

Inter-organizational knowledge transfer is among the main mechanisms through which firms search for knowledge (Rosenkopf & Almeida, 2003). The tacit and complex nature of knowledge however inhibits smooth knowledge transfer between organizations (Kogut & Zander, 1992; Polanyi, 1966). In this respect, recruitment of workers is considered an important way in which such complex knowledge is transferable between firms (Arrow, 1962) and enables firms to adopt new processes and introduce new products and services based on the inflow of new knowledge (Ettlie, 1985). This is in line with Simon (1991), who argues that "an organization learns in only two ways: (a) by the learning of its members, or (b) by ingesting new members who have knowledge the organization didn't previously have" (Simon, 1991: 125). Yet, hiring new employees does not equal organizational learning due to organizational routines and knowledge embedded in the social fabric of the firm (Kogut & Zander, 1992; Marengo, 1996). Consequently, scholars have become increasingly interested in how and when labor mobility affects organizational learning (Argote, 1999; Cohen & Levinthal, 1990; Palomeras & Melero, 2010).

Especially recruitment of highly-skilled individuals like inventors, engineers or scientists has been subject to scrutiny in the learning-by-hiring literature. Such individuals are expected to bring complex technical or scientific knowledge which may enhance or expand the current technological capabilities of hiring firms (Groysberg & Lee, 2009). In its original definition learning-by-hiring is defined as "the acquisition of knowledge from other firms through the hiring of experts" (Song et al., 2003: 352). Instead of this definition, we use a broader definition of learning-by-hiring, since we consider recruitment from both firms and universities. In particular firms active in knowledge-intensive industries that depend on advances in science, like biotechnology, may utilize university scientists to enhance in-house R&D efforts and explore new knowledge fields (Lacetera et al., 2004; Zucker & Darby, 1996). Most attention in this nascent stream of research has been paid to inter-firm knowledge transfer. Various studies indeed show that hiring firms draw upon the knowledge of previous employers of new recruits (Rosenkopf & Almeida, 2003; Singh & Agrawal, 2011; Song et al., 2003). Another claim made in this literature is that firms can overcome their predominant focus on local search or exploitative behavior through recruitment of highly-skilled workers, and thus serves as a measure to balance between exploitation and exploration (Rosenkopf & Almeida, 2003; Tzabbar, 2009).

The ability of a firm to explore new knowledge, for instance through recruitment, and create an innovation depends on its absorptive capacity (Cohen & Levinthal, 1990; Fabrizio, 2009). Absorptive capacity is defined as the "ability to recognize the value of new information, assimilate it, and apply it to commercial ends" and "is largely a function of the level of prior related knowledge" (Cohen & Levinthal, 1990: 128). In other words, the current knowledge base of a firm determines the firm's ability to explore the technological landscape, recognize valuable information, assimilate new knowledge with its current knowledge and transform it into an innovation. The concept of absorptive capacity has been further developed by Zahra & George (2002) who distinguish two types of absorptive capacity. Potential absorptive capacity refers to the valuation and acquisition stages of absorptive capacity, and the transformation and exploitation stages are captured by realized absorptive capacity (Zahra & George, 2002). While a firm may be able to identify and assimilate new knowledge, it is not necessarily able to transform and exploit the knowledge due to reasons we discuss below. To conclude, in-house activities, like R&D activities, improve the firm's ability to recognize, assimilate and exploit knowledge from outside the firm boundaries (Cohen & Levinthal, 1990).

In order to achieve effective knowledge transfer and create innovative ideas from new recruits, hiring firms need recruits that bring novelty as well as share similar knowledge. We therefore draw on the concept of optimal cognitive distance (Gilsing, Nooteboom, Vanhaverbeke, Duysters, & Vandenoord, 2008; Nooteboom, 2000; Wuyts, Colombo, Dutta, & Nooteboom, 2005). The concept of cognitive distance refers to the distance in how actors perceive, interpret, understand and evaluate the world according to mental frames (Wuyts et al., 2005). As cognitive distance increases between agents, opportunities for novel combinations arise. However, at some point increasing cognitive distance can become too large. That is, too high cognitive distance precludes mutual understanding and inhibits firms to create novel combinations from external knowledge. Thus, as cognitive distance increases, absorptive capacity decreases, but the novelty value increases. Nooteboom, Vanhaverbeke, Duysters, Gilsing, & Van Den Oord (2007) therefore propose an inverted-U shaped relationship between cognitive distance and innovation. In similar vein, Cohen & Levinthal (1990) argue that "some portion of that prior knowledge should be very closely related to the new knowledge to facilitate assimilation, and some fraction of that knowledge must be fairly diverse, although still related, to permit effective, creative utilization of the new knowledge" (Cohen & Levinthal, 1990: 136). Accordingly, firms need related variation in knowledge and skills to optimize the rate of learning (Dokko, Wilk, & Rothbard, 2009; Schilling, Vidal, Ployhart, & Marangoni, 2003).

Cognitive Distance between Worker and Hiring Firm

The contribution of a recruited R&D worker to the subsequent degree of exploratory innovation of the hiring firm may vary according to the knowledge characteristics of the worker and the hiring firm. The knowledge base of the hiring firm, as a result of experience with a specific set of knowledge components, determines its ability to assimilate and transform external knowledge acquired from R&D worker recruitment (Cohen & Levinthal, 1990). In similar vein, R&D workers are bound by their cognitive scope as a result of their education and accumulated skills over time. Consequently, the specific knowledge base of the R&D worker and hiring firm determine to what extent their knowledge bases are different or share knowledge components. We therefore utilize the concept of cognitive distance to capture the trade-off between novelty and absorptive capacity (Nooteboom, 2000). The learning-by-hiring literature that is devoted to explaining how recruitment affects inter-firm knowledge transfer shows that the higher the technological distance between the worker and the new employer, the more likely it is that recruitment will result in knowledge transfer between the previous and new employer (Palomeras & Melero, 2010; Rosenkopf & Almeida, 2003; Song et al., 2003). To illustrate this, Song et al. (2003) argue and empirically substantiate that recruitment of engineers is more likely to result in inter-firm knowledge transfer when the hired engineer possesses technological expertise distant from that of the hiring firm. In a study on alliances, Nooteboom et al. (2007) find an inverted U-shaped relationship between cognitive distance of alliance partners and the number of exploratory innovations. They argue that the cognitive distance between partners should be large enough to yield novelty, but not too large as too block mutual understanding. Or in other words, at a small cognitive distance, a firm has a high absorptive capacity, but the knowledge of the R&D worker brings little novelty. In contrast, a high cognitive distance between R&D worker and hiring firm lowers the absorptive capacity of the firm, but provides new knowledge which can be used in the R&D process. As a result, at some point the costs of low absorptive capacity may thus outweigh the advantages of increasing novelty; hence we expect an inverted U-shaped relationship. This leads to our first hypothesis:

Hypothesis 1: The cognitive distance between recruited R&D workers and hiring firm has an inverted U-shaped relationship with the subsequent degree of exploratory innovation

Employee Diversity of the Hiring Firm

A firm's diversity among employees has recently received increasing attention in the search literature since such diversity gives rise to novel recombinations of different components of knowledge, and subsequently foster the innovative capabilities of the firm (Laursen, forthcoming; Parrotta, Pozzoli, & Pytlikova, 2010; Østergaard, Timmermans, & Kristinsson, 2010). However, at some point increasing employee diversity comes at the expense of communication, coordination and mutual understanding, because there is a lack of common language and understanding, and no shared approach to codifying knowledge. This suggests an inverted U-shaped relationship between employee diversity and innovative capabilities (Laursen, forthcoming; Østergaard et al., 2010).

We instead examine how employee diversity affects the relationship between recruitment and exploratory innovation. A diverse group of employees in terms of skills and education is likely to affect the firms' ability to assimilate external knowledge from recruited R&D workers (Zahra & George, 2002). In other words, a hiring firm with a varied group of workers is more likely to adopt new ideas from recruited R&D workers than a uniform group. We expect that employee diversity moderates the inverted U-shaped relationship between cognitive distance and exploratory innovation in two ways. First, increasing diversity will increase the strength of the positive relationship between cognitive distance and exploratory innovation, because low levels of cognitive distance are combined with high diversity and thus allows for knowledge recombination. Second, increasing diversity will increase the strength of the negative relationship between cognitive distance and exploratory innovation. A high diversity is combined with a high cognitive distance and is hence likely to result in communication problems as a result of a lack of common understanding. We therefore hypothesize:

> *Hypothesis 2: Employee diversity at the hiring firm moderates the inverted U-shaped relationship between cognitive distance and subsequent exploratory search in such a way that increasing diversity will (a) increase the slope of the positive effect of cognitive distance, and (b) increase the negative effect of cognitive distance*

3. METHODS

Data and Sample

In order to test these hypotheses, we measured the degree of exploratory innovation as a function of the cognitive distance of recruited R&D workers, firm characteristics and control variables. Our empirical analysis draws on a combination of three datasets. First, we utilized the Danish Integrated Database for Labor Market Research (IDA being its Danish acronym). This is a detailed employer-employee register database, annually updated (i.e. November each year), from 1980 onwards (Timmermans, 2010). The individual-level data provided us with annual data on worker mobility and the background of workers. Second, the Firm Integrated Database (FIDA) provided us with firm-level controls. Finally, we used patent application data from the European Patent Office (EPO) to determine the degree of exploratory innovation as well as several controls.

We merged the patent data with IDA and FIDA on the firm-level. Due to a structural break of unique firm identifiers in IDA in 1999 and lags in reporting at the European Patent Office (EPO) our final dataset consisted of all Danish R&D active firms, their patents and labor flows for the period 1999-2004. The database allowed us to directly measure R&D worker recruitment in the Danish economy. We specifically focused on firms that patent in the period 1999-2004 to construct the measure of exploratory innovation.
The sample does not include all Danish firms, but only R&D active firms (i.e. firms with at least one R&D worker) that patented during the period 1999-2004. We focused on R&D active firms, because firms without any R&D worker are unlikely to patent, as discussed in previous studies with similar datasets (e.g.: Ejsing, Kaiser, & Kongsted, 2011; Kaiser, Kongsted, & Rønde, 2011). Prior work on a similar dataset showed that 95 percent of the Danish patenting firms are R&D active (Kaiser & Schneider, 2004).
We utilized patent application data from EPO, better known as Patstat data, to identify the technological activities of the R&D active firms, although not all innovations are patented (Wu, 2011). Patent data has been widely used to measure inventive output (Griliches, 1990). Our focus on a single country, Denmark, maintains reliability, consistency and comparability across firms (Griliches, 1990; Yang, Phelps, & Steensma, 2010).
R&D workers are defined as individuals that occupy positions involving a high level of scientific and technological activity, and therefore demand a high level of skills (based on the Danish version of the International Standard Classification of Occupations, DISCO). In addition to this, we required that R&D workers are full-time employed persons between 20 and 75 years with a technical degree, bachelor degree or a higher obtained degree within a relevant study area (i.e. technical, natural, veterinary, agricultural or health science). We considered R&D workers hired from both firms and universities. Instances of recruitment of R&D workers are observed every November each year.
We were able to identify and match 2545 organizations and 11065 patents for the period 1978-2004. Within the period of study, 1999-2004, we find 1289 organizations that generated at least one patent. We limited the sample to firms that patented sufficiently (i.e. three times) in the five-year period following prior research, in order to reliably assess exploratory behavior (e.g. Tzabbar, 2009). Firms should furthermore have at least one R&D worker. Our final sample counts 249 firms and 751 firm-year observations.

The Dependent Variable

Exploratory Innovation. The dependent variable represents the creation of novel knowledge relative to its existing knowledge stock. The level of exploratory search is measured at the firm-level utilizing patent citations from patent applications, which is in line with previous studies (Benner & Tushman, 2002; Katila & Ahuja, 2002; Phelps, 2010; Rosenkopf & Nerkar, 2001; Wu, 2011). Patent applications are preferred over patent grants, because applications provide better insight into the variety of technological activities of firms, and hence are a good indicator of exploratory technological activities (Belderbos, Faems, Leten, & Looy, 2010). For each firm i in year t we retrieved the backward citations from the patent applications. We determined for each citation whether it has been used by the firm prior to the patent application. In line with previous research we use a five-year window to assess exploratory behavior (e.g.: Katila & Ahuja, 2002). The variable is computed as the number of new citations divided by the total citations for firm i in year t. Thus, our measure is as follows:

$$Exploratory\ innovation_{it} = \frac{no. of\ new\ citations_{it}}{total\ citations_{it}}$$

Our measure represents the share of new citations and not a count of exploratory inventions as for instance used by Gilsing et al. (2008) and Nooteboom et al. (2007). Our measure rather captures the propensity to generate exploratory innovations, independent of firm scale (Phelps, 2010: 898). Moreover, our measure is consistent with theory that views exploration and exploitation as two ends of a continuum (Lavie et al., 2010).

Explanatory Variables

Cognitive Distance. The effect of R&D worker recruitment is measured by the cognitive distance between recruited R&D workers and hiring firm. To determine the cognitive distance between hiring firms and the R&D workers that join these firms we follow methods developed for patent-based studies. More specifically, Jaffe (1986) developed a procedure to determine the technological position of firms. He utilized the distribution of patents of firms over patent classes to generate a vector that describes the firms' technological position. Instead of using patent classes we use the educational backgrounds of each firms' R&D worker (see for examples that use patent classes: Benner & Waldfogel, 2008; Kaiser, 2002; Sampson, 2007; Tzabbar, 2009). We assume that the educational background represents the knowledge embodied in a R&D worker. Consequently, the cognitive position of the hiring firm is represented by a vector that counts the percentage of R&D workers in a specific educational class. Thus, by using the distribution workers across educational classes, we aim to capture differences in the cognitive scope between the group of recruited R&D workers and the R&D workers already present in the firm, measured November each year. We use 16 4-digit educational classes to determine the cognitive distance of workers. The educational classes are based on the workers' highest completed degree.

We measure the cognitive distance between the group of recruited workers (vector F_i) and the hiring firm (vector F_j) as angular distance. The multidimensional vector $F_i = (F_i^1 \dots F_i^s)$, where F_i^s represents the number of R&D workers in educational class s. This vector is updated for each year in the period 1999-2004. The formula of cognitive distance is as follows:

$$Cognitive\ distance_{ij} = cos^{-1} \frac{F_i \times F_j}{\sqrt{F_i^2} \times \sqrt{F_j^2}}$$

Where i represents the recruited R&D worker(s) and j represent the R&D worker(s) already present in year t. Our measure varies from 0 to 1.57, where a value of 0 is full overlap (i.e. identical cognitive scope) and our maximum value is no overlap (i.e. distant). This measure is not sensitive to the population in a specific class (Sampson, 2007). Note that this measure does not take into account the relatedness between specific educational classes, but rather measures the overlap in distribution of R&D workers across educational classes. Because exploratory search is a process, we do not expect short-term effects from R&D hires on the innovation process. Therefore we lag cognitive distance twice.

Employee Diversity. The diversity of each firm's workforce is defined by the heterogeneity of the R&D workers' educational background. We utilize the Herfindahl index, a common measure which in our case takes into account the number of 8-digit educational classes a firm possesses and how equally populated those classes are with R&D workers. Let firm i have N_i R&D workers with educational background j at time t. The employee diversity is then defined as follows:

$$1 - \sum_{j=1}^{J} \left[\frac{N_{ij}}{N_i}\right]^2$$

The value of employee diversity ranges between 0 and 1. The higher the value of this index, the higher the employee diversity at firm i in year t.

Control Variables

Technological Breadth. Firms characterized by broad search practices are likely to do so in the future (Laursen et al., 2010; Tzabbar, 2009). We account for search breadth by utilizing the degree of dispersion of the firm's patents across 4-digit patent classes of the five years prior to the end of year t. The Herfindahl measure varies between 0 and 1.

Co-patenting. To account for other forms of formal or informal external sources than R&D worker recruitment we include a dummy variable that is equal to 1 if firm i co-patented in time t.

Firm patent stock. We account for the patenting experience of firms by measuring the patent stock of firms, including the pre-sample (1978-1999). This measure captures prior spending on R&D and a firm's propensity to patent (Sampson, 2007).

Sales. We control for any effect that stems from firm size by taking the natural logarithm of the firm's sales.

Firm Age. As firm age increases firms tend to show less exploratory behavior (Almeida, Dokko, & Rosenkopf, 2003; March, 1991). We measure age as the logarithm of number of years since date of founding.

Industry. Any industry effects are accounted for by industry dummies.

Capital region. Any effect that stems from regional variation in patenting behavior as well as exploratory search processes is accounted for by a dummy variable. The variable denotes whether a firm is located in the Copenhagen capital region or not.

Model Specification and Estimation

The dependent variable, exploratory innovation, is a proportion which is naturally bounded between 0 and 1. We therefore apply a so-called fractional response model (see for applications Phelps, 2010 and Wu, 2011). Fractional response models account for the fact that proportions are naturally bounded and have values at the boundaries, which raise issues in terms of inference and functional form (Papke & Wooldridge, 1996; Papke & Wooldridge, 2008; Wooldridge, 2002: 748-755). Thus, we estimated models using a generalized estimation equation (GEE) with a probit link function (Papke & Wooldridge, 2008). Alternatively, we estimated a panel linear regression with robust standard errors. They yield similar results.

4. RESULTS

The means, standard deviations, minimum and maximum values, as well as correlations are presented in table 1. No correlation is critically high. The variables sales and age have high VIF values, but the results remain the same when the variables are demeaned. The average VIF is below 4. Even though cognitive distance and employee diversity are based on the same variable, but different numbers of digits, (4 and 8-digit respectively), the correlation table shows a correlation of .39, which is not considered high. The panel data was unbalanced and included 249 firms and 751 firm-year observations. Because we lag the main explanatory variables twice we lose observations and the estimation is limited to 172 firms and 405 firm-year observations.

Table 1

Descriptives and correlations[a]

Variables	Mean	s.d.	Min.	Max.	1	2	3	4	5	6	7	8	9
1. Exploratory innovation	0.12	0.23	0	1	1								
2. Cognitive distance$_{t-2}$	0.34	0.40	0	1.57	.08	1							
3. Employee diversity$_{t-2}$	0.39	0.22	0	0.72	.00	.39	1						
4. Techbreadth	0.21	0.32	0	0.96	.02	-.01	.30	1					
5. Co-patenting	0.06	0.24	0	1	.03	.05	.11	.09	1				
6. Firm patent stock[b]	2.41	1.32	0	7.26	-.01	.03	.21	.65	.09	1			
7. Sales[b]	18.16	3.99	0	23.98	-.09	-.09	.25	.26	.04	.40	1		
8. Firm age[b]	2.71	1.09	0	4.64	-.06	.10	.37	.31	.01	.48	.52	1	
9. Capital region	0.53	0.50	0	1	.06	.18	.32	.13	.27	.27	-.16	.01	1

[a] n= 751. Correlations above .09 are significant at $p<.05$

[b] Logarithm

Table 2 displays the preliminary results of our fractional response models. Model 1 shows the control variables. As is shown in Model 1, the coefficient estimates of firm age and patent stock are negative and significant (at the 10% and 5% level respectively). This suggests that older firms and firms that have a longer patent experience are less likely to generate exploratory innovations. This is in line with previous research. Hypothesis 1 predicted an inverted U-shaped effect of cognitive distance on subsequent exploratory innovation. Models 2 to 6 provide support for this hypothesis. Cognitive distance$_{t-2}$ showed a positive and significant effect (at the 5% level) on explanatory innovation in all the models. In addition, the squared term is negative and positive in the respective models, which suggests there is a curvilinear effect of cognitive distance on exploratory innovation. Hypothesis 2 hypothesized a moderation effect of employee diversity at the time of hiring. We include employee diversity$_{t-2}$ in models 4 to 6. Employee diversity$_{t-2}$ is not significant, which suggests there is no direct effect of employee diversity on subsequent exploratory innovation. To explore the contingent relationship, we created two interaction effects and included the main effects and interaction terms in model 5 and 6. They show there is no moderation effect of employee diversity$_{t-2}$. The Wald statistics do not improve by adding the main variables in models 2 to 6 compared to the control or baseline model. This could be the result of having fewer observations in models 2 to 6. We also estimated other models where we added cognitive distance and employee diversity with one lag. They were insignificant and are therefore not reported here.

Table 2

Results of Fractional Response Model Predicting Exploratory Innovation[a]

Variables	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
Technological breadth	.23	(.34)	.46	(.43)	.40	(.44)	.46	(.44)	.39	(.43)	.32	(.44)
Firm sales[b]	.01	(.02)	-.01	(.03)	-.01	(.03)	-.01	(.03)	-.01	(.03)	.00	(.03)
Firm age[b]	-.15†	(.08)	-.11	(.12)	-.19	(.13	-.14	(.13)	-.14	(.13)	-.15	(.13)
Co-patenting	.21	(.42)	.35	(.53)	.25	(.53)	.28	(.53)	.20	(.56)	.17	(.54)
Firm patent stock[b]	-.00*	(.00)	-.00	(.00)	-.00	(.00)	-.00	(.00)	-.00	(.00)	-.00	(.00)
Farm & food	Baseline		Baseline		Baseline		Baseline		Baseline		Baseline	
Textiles & paper	-.55	(.44)	-.17	(.71)	.20	(.72)	.09	(.69)	.13	(.70)	.20	(.70)
Chemicals	-.31	(.47)	-.33	(.68)	-.28	(.68)	-.28	(.53)	-.24	(.68)	-.17	(.69)
Plastic & glass	.16	(.42)	-.61	(.59)	.84	(.59)	.85	(.59)	.85	(.58)	-.87	(.57)
Metals	-.00	(.44)	-.10	(.67)	.16	(.66)	.15	(.68)	.17	(.66)	.17	(.64)
Machinery	-.38	(.39)	-.26	(.62)	-.06	(.62)	-.05	(.61)	-.08	(.62)	-.03	(.60)
Electronics	-.36	(.43)	-.25	(.68)	-.10	(.67)	-.07	(.67)	-.10	(.67)	-.00	(.66)
Instruments	-.41	(.43)	-.62	(.64)	-.40	(.64)	-.39	(.64)	-.40	(.64)	-.41	(.62)
Gross & retail trade	-.09	(.50)	-.23	(.77)	-.05	(.78)	-.04	(.78)	-.00	(.78)	.03	(.76)
Vehicles	-.71	(.51)	-1.83	(1.16)	-1.77	(1.25)	-1.78	(1.20)	-1.78	(1.23)	-1.72	(1.22)
Furniture	-.82	(.76)	-.27	(1.22)	.10	(1.25)	.08	(1.14)	0.07	(1.20)	0.04	(1.26)
IT & telecom	-.16	(.47)	.22	(.59)	.38	(.58)	.34	(.58)	.34	(.58)	.34	(.58)
Technical services	-.14	(.41)	-.13	(.60)	.02	(.60)	.08	(.61)	.12	(.60)	.18	(.59)
Business-related services	-.14	(.57)	.07	(.94)	.34	(.95)	.25	(.95)	.35	(.96)	.46	(.96)
Other	1.23**	(.38)	.58	(.64)	.84	(.66)	.94	(.67)	.68	(.70)	.49	(.69)
Capital Region	.06	(.17)	.19	(.21)	.10	(.22)	.14	(.22)	.11	(.23)	.16	(.23)
Cognitive distance$_{t-2}$			.42*	(.21)	2.18*	(.86)	2.7**	(.99)	2.7**	(.99)	2.26**	(.97)
Cognitive distance sq.$_{t-2}$					-1.41*	(.64)	-1.73*	(.72)	-1.71*	(.72)	-1.70*	(8.71)
Employee diversity $_{t-2}$							-.54	(.45)	-.50	(.48)	-.55	(.48)
Cognitive distance $_{t-2}$ x employee diversity $_{t-2}$									-.90	(.75)	-3.34	(2.12)
Cognitive distance sq. $_{t-2}$ x employee diversity $_{t-2}$											1.97	(1.77)
Observations	751		405		405		405		405		405	
Firms	249		172		172		172		172		172	
Wald X2	287.72***	(20)	65.11***	(21)	76.65***	(22)	89.22***	(23)	79.42***	(24)	86.11***	(25)

[a]n=751. Correlations above .09 are significant at $p<.05$

[b]Logarithm

† $p<.10$, $^{*}p<.05$, $^{**}p<.01$, $^{***}p<.001$

5. DISCUSSION AND CONCLUSION

In this study we examine the effect of cognitive distance, between new R&D hires and hiring firms, on subsequent exploratory innovation. The origins of exploratory search processes are far from established, especially with regard to firms' hiring processes. Drawing on search, absorptive capacity and cognitive distance literature we predicted that there is an inverted U-shaped relationship between cognitive distance and subsequent exploratory innovation. Findings from the analysis showed that the cognitive distance of hired R&D workers in t-2 have a curvilinear effect on the firm's subsequent exploratory innovation at time t. Moreover, we examined employee diversity at the moment of hiring as possible moderator of the relationship between cognitive distance and subsequent exploratory innovation. The findings suggest employee diversity does not affect this relationship.

To our knowledge this is the first study to test and find a curvilinear effect of cognitive distance, based on hiring of R&D workers, on subsequent exploratory innovation. This study and in particular this finding has implications for different bodies of literature. First, this study contributes to the learning-by-hiring literature. Our findings indeed suggest that firms could leverage their new hires' knowledge in order to spur exploratory innovation. This is in line with previous studies that focus on the relationship between hiring and organizational learning (e.g. Rosenkopf & Almeida, 2003; Song et al., 2003; Tzabbar, 2009). Yet, none of these studies has shown a curvilinear effect of R&D worker recruitment on exploratory innovation. That is, firms could benefit from hiring distant R&D workers, but only up till a certain point where too much distance worsens subsequent exploratory innovation.

Second, this study also adds to a better understanding of how firms can overcome local search bias (Levinthal & March, 1993; Stuart & Podolny, 1996). Such bias comes at the expense of more exploratory, and diversity inducing, search processes which are important for the adaptability and survival of the firm. Our study suggests that hiring highly skilled workers with different educational backgrounds compared to already present R&D workers generates future innovations that seem to build on more non-local search processes. This complements previous research on for instance alliances and licensing (e.g. Phelps, 2010). Also, our results strengthen the idea that search is a timely process.

Third, the rich data on Danish firms, their hiring practices and patenting behavior enables us to proxy cognitive distance based on the workers highest fulfilled educational degree. This advantage allows to empirically substantiate the idea that there is an optimal cognitive distance in relation to learning and innovation (Nooteboom, 2000).

The preliminary results and contributions should nevertheless be considered in light of the limitations of this study. First, the use of patent citation data to measure exploratory search processes has limited suitability. We can only proxy exploratory search processes by measuring the novelty of new patents compared to previous patents (Laursen, forthcoming: 19). Moreover, firms may not patent all innovations.

Second, even though our analysis is based on a 5-year period, which allows us to explore the effect of hiring on exploratory innovation over time, we do not have many observations in our sample. We need to limit the sample to firms that patent sufficiently in the period of study to measure exploratory innovation properly.

Third, one could argue to what extent educational background captures a worker's cognition. The fact that some workers have gained industry experience in which they did not use their specific knowledge and skills obtained during their studies, may affect our results. Yet, the educational background may still capture how a worker perceives, interpret and understand the world in later stages of his or her life. Likewise, one could argue that the sum of educational backgrounds of R&D workers, already present at the firm, may not capture a firm's knowledge base. Yet, we believe that the comparison of the R&D workers' educational background is a novel and interesting way to measure their distance in comparison to workers that are already present in the R&D department of a firm.

Fourth, one of the main concerns with these preliminary results is that our analysis may be affected by endogeneity. Endogeneity occurs when a regressor is correlated with the error term (Bascle, 2008; Hamilton & Nickerson, 2003). We specifically need to deal with endogeneity of the firm's decision to hire a distant R&D worker. The decision to hire a R&D worker might be correlated with unobservable factors that also influence the exploratory behavior of R&D firms. Strategic decisions made by managers are among the possible unobserved factors that may affect recruitment of R&D workers and also affect exploratory behavior of firms. Or, in other words, firms that have adopted a new strategy may simultaneously lead to the decision to recruit distant R&D workers. Consequently, firms that choose to change strategy will select into hiring new distant R&D workers (Lacetera et al., 2004; Rao & Drazin, 2002; Singh & Agrawal, 2011; Tzabbar, 2009). This is better known as omitted variable bias with self-selection being the source (Wooldridge, 2006).

A final limitation is that this study is still in its initial stage, and that the results have not been subject to robustness checks. Neither do we consider alternative explanations for our preliminary findings yet.

6. FUTURE DIRECTIONS OF THE PAPER

Some future ideas about this paper are as follows. First, an increasing literature on labor mobility, skill relatedness and firm performance use industry classifications as common measure to capture the relatedness of skills and knowledge in comparison to the hiring firm (e.g. Boschma, Eriksson, & Lindgren, 2009; Timmermans & Boschma, 2010). Industry classifications of firms are used to determine whether hired workers are from a similar, related or unrelated industry. We could compare our cognitive distance measure with the taxonomy based on industry relatedness and see how they relate to each other.

Second, our second hypothesis on employee diversity has been operationalized as diversity based on educational classes. We could also explore diversity based on age or tenure (e.g. Østergaard et al., 2010), as well as use different measures that take into account separation, variety or disparity (e.g. Harrison & Klein, 2007).

Third, endogeneity remains an issue that needs to be addressed. A possible strategy to address endogeneity is using a two-stage Heckman selection procedure, in conjunction with or without instrumental variables (Bascle, 2008; Lacetera et al., 2004; Tzabbar, 2009).

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