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Relatedness through experience: On the importance of collected worker experiences for plant performance

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Abstract

The present article aims to show that multiple cognitive dimensions exist between employees in plants and that these multiple forms of potential cognitive relatedness interact in their influence on learning and plant performance. Because the success of a firm has come to be strongly associated with its ability to use the available resources (Penrose 1959), it has become increasingly important for firms to have just the right mix of competences. In the article, the knowledge and cognitive distance between employees in knowledge-intensive business services (KIBS) is measured in multiple ways – as formal knowledge, industry experience and past knowledge exposure. The different forms of cognitive distance are entered into pooled OLS regressions with year-, industry-, region-fixed effects and interaction terms to estimate the effects of various forms of cognition on plant performance. The results suggest that past knowledge experiences and formal education offer multiple channels for knowledge integration at the workplace and that the specific labor force knowledge characteristics present at a plant condition learning. It has been further shown that the organizational structure and flexibility associated with single-plant and multi-plant firms, respectively, generate different plant performance outcomes of knowledge variety. Moreover, we conclude that the commonly found negative effects of similarity in formal education on plant performance may be reduced by high levels of similarity in historical knowledge exposure or industry experience. These effects are stronger in multi-plant firms than in single-plant firms. We also find that high levels of human capital exert a reducing influence on the negative effects of high levels of cognitive similarity.

Keywords: Cognitive proximity, plant performance, KIBS, human capital, proximity dimensions

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Introduction

Because the success of a firm has come to be strongly associated with its ability to use the available resources (Penrose 1959), it has become increasingly important for firms to have just the right mix of competences. Therefore, the role of knowledge and knowledge structures within and between firms and regions has surfaced as an important research area for better grasping the contingent nature of innovation and competitiveness (Balland et al. 2013; Neffke and Henning 2013; Neffke et al. 2011). With regard to the vast interest in knowledge as a resource, there is a wide body of literature discussing cognitive distance between agents as an important factor for knowledge transfer, learning and innovation (Boschma 2005; Harrison et al. 2001; Nooteboom et al. 2007; Tanriverdi and Venkatraman 2005; Wuyts et al. 2005). However, while it is generally agreed that human capital positively impacts performance, we still know little about to what extent particular types of in-house competence portfolios influence plant performance (Lacetera et al. 2004). In one of the few empirical studies on this topic, Boschma et al. (2009) suggest that it is not human capital concentrations *per se* that are of importance for productivity, but rather the degree of cognitive relatedness between employees.

The aim of the present article is to add to this literature by assessing the role of the past work experiences of individuals in plant performance. We compare the effects of relatedness in experiences with the effects of both relatedness in formal skills (education) and human capital ratio on plant performance. In empirical studies, labor mobility is often used as a proxy for the circulation of knowledge in space (e.g., Eriksson 2011; Timmermans and Boschma 2013; Östbring and Lindgren 2013), and cognitive distance is commonly measured as relational differences in formal education or sector belonging between individuals and firms (Boschma et al. 2009). This type of data only reflects a certain aspect of an individual’s skills and abilities, namely that exemplified by formal education, profession or industry experience prior to the job change. This is unsatisfactory, because the literature clearly indicates that skill matching is a key issue for learning and innovations to occur within firms (Nooteboom 1999) as well as regions (Boschma et al. 2014). When using micro-data, an assumption is made that individuals who have graduated from a specific vocational training or university program are identical and fully exchangeable. This assumption does not hold, not even on the day of graduation, and they will most likely diverge even more as they take on different jobs in different contexts. This is variation that should be taken into account when analyzing relatedness in the work force.

From an evolutionary point of view, the history of the region is important in understanding the current industry setup and potential future paths, but we argue that the history of the individuals should also be considered. The continuous modification of firm paths is the result of decisions made by actors within the firm (Strambach 2010). These individuals – the labor force – are small units of cognitive abilities and experiences that are continuously being reproduced (Storper and Walker 1989) and that shape the firm and the territorial development (Storper 1995). The work experiences that each worker carries with her render the sum of those skills exclusive to that individual. But, experience also translates into familiarity with one or a few different practices and modes of knowledge application. We hypothesize that past industry experiences and knowledge exposure also affect an individual's cognitive ability and her capacity to apply theoretical knowledge and to understand and conform to different practices. Therefore cognitive relatedness can be achieved and measured in more than one way. Furthermore, we theorize that the role of in-house knowledge and relatedness in plant performance differ between single-plant and multi-plant firms. In multi-plant firms each plant represents a part of a greater knowledge pool available within the firm. Thus, the role of knowledge within the plant is potentially suppressed by the greater knowledge availability within the firm. Finally, we suggest that the different forms of cognitive ability and relatedness have potential overlap effects; high levels of relatedness in one type of cognitive ability may either abate or promote the effects of relatedness in another type of cognitive ability. If this is the case, the present article could help explain the slightly diverging results of existing studies on the effects of labor force skills and knowledge on firm performance. To our knowledge, existing studies have used only one measure of cognitive relatedness without controlling for other forms of cognitive relatedness that can facilitate communication and learning.

The empirical analysis is based on geo-referenced longitudinal matched employer-employee data. We examine the competence structure in knowledge-intensive business services (KIBS) in Sweden between 2000 and 2010. In addition to determining the human capital ratio and entropy measures of variety of formal in-house competences (education of employees), we trace former workplaces and co-workers of individual employees and estimate the variety of knowledge exposure and industry experience, respectively. The effects of the different forms of cognitive relatedness on plant performance are estimated using pooled OLS regressions with cluster robust standard errors and year-, region-, and industry-fixed effects. Interaction terms are used to determine the overlap effects.

The paper is structured as follows: After the introduction, Section 2 presents the view that knowledge and experience jointly affect the collaborative abilities and potential for knowledge application within firms. Section 3 presents the data and model, and Section 4 the empirical results. Section 5 concludes the paper.

Knowledge reproduction and knowledge transfer

The firm is constantly evolving, trying to stay competitive by acquiring new knowledge and applying existing knowledge in new ways (Spender 1991). However, knowledge as a resource is not only determined by the technological regime associated with industry and sector belonging, but is also socially and territorially embedded (Bathelt and Glückler 2012; Gertler 2003; Granovetter 1985; Maskell and Malmberg 1999; Nooteboom 1992; Rigby and Essletzbichler 2006; Storper 1995). This makes knowledge different from material resources, in that it is embodied in people who are embedded in contexts (Amin and Cohendet 2005; Farole et al. 2010; Grabher and Ibert 2014; Howells 2012; Lam 1997). Thus, learning and the potential innovative power of interaction are conditional on the abilities and experiences of the participating agents. Lacetera et al. (2004) demonstrated that single, "high-ability" individuals not only contributed their own knowledge to innovation, but also had an impact on the skills of other employees, thus changing the overall capabilities of the firm.

Insofar as knowledge transfer and learning have been explored quantitatively, labor mobility has been used as a proxy for knowledge flows and there has been a tendency for learning to be defined either as a change in productivity or patents. Labor mobility studies are becoming increasingly popular since labor mobility has proven to be an efficient channel for dissemination of knowledge (Szulanski 1996) across the entire tacit/explicit continuum (Polanyi 1966). Among others, Almeida and Kogut (1999), Breschi and Lissoni (2009), Eriksson and Lindgren (2009), Maliranta et al. (2009), Song et al. (2003) and Timmermans and Boschma (2013) have studied person-embedded knowledge, its transfer through labor mobility and its effect on productivity and innovation. Almeida and Kogut (1999) showed that the mobility of engineers influenced local transfers of knowledge. Building on these findings, Breschi and Lissoni (2009) showed that the localization effects of simply being co-located were diminishingly small when controlling for the mobility of inventors, thus putting forward the idea that labor mobility is the *main* conductor of local knowledge transfer. Eriksson and Lindgren (2009) confirm this notion in their study on the impact of labor flows on plant productivity in all parts of the Swedish economy. Their results indicate that not only inventors are crucial to understanding the role of mobility, because all types of labor flows contribute to plant performance more than do “pure knowledge externalities” that reside “in the air” of agglomerations. Boschma et al. (2009, 2014) further developed this suggestion by demonstrating that type of knowledge matters to understanding the impact of knowledge flows on firm performance and growth. In this respect, particularly labor flows from related sectors had a positive impact on plant performance. Whereas Boschma et al. (2009) studied the entire Swedish economy other studies have found varying effects of related variety on innovation and performance in different sectors (e.g., Bishop and Gripaios 2009; Östbring and Lindgren 2013). These findings support the notion that sectors constitute unique technological contexts that are asymmetrically influenced by relatedness in the labor force and the regional industry setup. The reason for this is most likely different possibilities for interactive learning and application of ideas in production processes in the different sectors. In this article firms in KIBS are analyzed in order to isolate the effect of learning on plant performance in this sector. These firms have a change focus and knowledge and creative solutions are their main input as well as output, thus any changes in plant performance are highly likely to result from learning processes.

Boschma et al. (2009) also showed that having a cognitively related in-house staff was more important to productivity than was having a high human capital ratio. Nevertheless, the competence within the firm and how it influences performance and localized learning still remains something of a black box. This is the case despite the fact that firms are believed to structure learning processes and act as repositories of knowledge (Maskell 2001). The structuring aspect of the firm and its routines is a factor that creates different possibilities for knowledge transfer and knowledge application in firms with different corporate cultures. But the structures and flexibility of firms also depend on whether the firm has one or more plants to administrate. Hakkala (2006) found labor productivity growth in multi-plant firms to depend mainly on the organizational flexibility, i.e. the freedom to acquire productive plants and rid of unproductive plants. Administration and management decisions are, to a larger extent than for single-plant firms, decisive factors for the performance of multi-plant firms. Such factor are often external to the plant, while influencing the internal plant productivity. Furthermore, multi-plant firms have a greater internal knowledge pool at their disposal. This is especially true for multi-plant firms in KIBS where the function of each plant is similar to the others within the firm. In a recent article by Rigby and Brown (2015) it was also found that multi-plant firms did not benefit from agglomeration externalities (access to a specialized and qualified labor force is one such advantage) but rather from the extended buyer-supplier networks that multi-location firms enjoy. This too is a factor that is potentially external to the plant in multi-plant firms, but will contribute to promoting performance, nonetheless. Therefore, we expect the overall impact of knowledge variety on plant performance to be larger in single-plant firms. On the other hand, human capital may play a greater role in multi-plant firms where skills in communicating, accepting and applying decisions made elsewhere are important to plant performance.

The presumed reason for the positive effects of acquiring related pieces of knowledge is individuals' potential to use their overlapping knowledge to communicate their unique knowledge and thus generate novelty (Nooteboom 1992). There is a growing body of literature discussing proximity dimensions (Boschma 2005; Torre and Gilly 2000; Hansen 2012; Song et al. 2003) as important factors for intra- and inter-firm learning. These proximities offer multiple ways of constructing shared values between individuals and potentially also a shared basis for communication and learning. Furthermore, there is a coherent body of literature, ranging over several fields, that discusses the benefits of relatedness with reference to both learning and firm productivity and competitiveness (Boschma et al. 2012; Harrison et al. 2001; Heimeriks and Boschma 2013; Markides and Williamson 1994; Neffke et al. 2012; Nonaka et al. 2000; Nooteboom 1992; Nooteboom et al. 2007). In its simplest form, the relatedness idea proposes that individuals with very different pieces of knowledge are unable to understand each other and will not be able to advance either their own knowledge or the knowledge of others. Individuals with similar knowledge, on the other hand, will understand each other perfectly, but are unable to achieve interactive learning. Consequently, individuals with related skills and knowledge are able to understand one another while simultaneously drawing on each other's knowledge to advance their own, and thus promote learning. In a Penrosian perspective, in-house knowledge and firm structure constitute the unique capabilities that equip seemingly similar firms with utterly different opportunities (Penrose 1959), and location-specific competitive advantages (Maskell 2001). We argue that just like an inflow of related competences is efficiently absorbed into the existing knowledge pool, a varied but related in-house competence portfolio should offer a breeding ground for new ideas and potentially new firm capabilities.

When Cohen and Levinthal (1990) coined the expression absorptive capacity, they claimed that it was largely determined by individuals' cognitive abilities, the *relatedness* of their knowledge and the heterogeneity of their collected experiences. The same labor force characteristics are also major determinants of the ability to collaborate internally, within the firm (March 2010; Nooteboom 2004). An individual's cognitive ability is an outcome of his/her formal knowledge and past work experiences. Past work experiences equip employees with unique sets of skills stemming from previous professions, industry belongings and interactions with co-workers. The in-house ability to generate and apply knowledge and thus remain competitive has been called 'intellectual collaboration' by Nooteboom (2009) and 'combinative capabilities' by Kogut and Zander (1992). These concepts fit into the general discussion of dynamic capabilities in the knowledge-based theory of the firm (Grant 1996b; Teece 2007), according to which knowledge integration is perceived as the primary role of the firm (Grant 1996a). Whereas absorptive capacity entails interpreting and learning, intellectual collaboration also involves teaching and communicating in a reciprocal manner. High abilities in intellectual collaboration potentially generate beneficial prerequisites for continuous advancements of firm knowledge (Nooteboom 2009) and thus innovativeness.

The abilities of employees to collaborate intellectually and advance their own as well as "the total" knowledge within the firm can be conceived of as combined knowing in practice (Orlikowski 2002). As such, knowledge is highly dependent on the participating agents and their ability to act in accordance with current practices, because it is not until knowledge is *applied* that it becomes a valuable resource to the firm (Grant 1996a, 1996b). Thus, a shared practice enables development and promotes the application of ideas. Becker (2004) argues that one way to construct a shared practice is through distributed firm routines, which represent physical and mental structures that are known to everyone within the firm. Boschma (2005) suggests that related knowledge between individuals results in coherence in knowledge views and a good ability to communicate. We add the assumption that employees with related industry experiences and/or related past knowledge exposure offer access to other practices from which lessons can be learned and processes modified. Similar to relatedness in formal knowledge, relatedness in industry experience or knowledge exposure generates productive communication and a basic understanding of the knowledge of others. In addition to this, relatedness in industry experience or knowledge exposure also helps employees evaluate the functionality and feasibility of ideas. It potentially also fosters trust between employees through familiarity with the "others'" knowledge, which allows more far-fetched ideas to be discussed and potentially acted upon and implemented. Thus, we hypothesize that relatedness in all forms of knowledge enables efficient communication and learning, whereas relatedness in industry experiences and knowledge exposure also offers the potential to find multiple applications for existing bits of knowledge and thus renewal of plant capabilities. Employees' past experiences are essential in forming individuals' own abilities to seize ideas, communicate them and transform them into productive practice. Cognitive proximity can therefore be measured in multiple ways, which capture different aspects of knowledge promotion and innovativeness. It is likely that proximity in one type of cognitive ability influences the effects of the other types of cognitive abilities on plant performance, e.g. proximity in previous knowledge exposure among employees may abate the negative effects of a high degree of unrelatedness in formal education. That is to say, there are overlap effects between different forms of cognitive proximities.

When we compare existing empirical studies on the cognitive distance between workers, we find inconsistent results. This indicates that there is potentially more to cognitive abilities than has been operationalized and empirically tested so far. For example, Boschma et al. (2009) found related skill inflow to be the most economically beneficial to a plant, Timmermans and Boschma (2013) found related skill inflow to be detrimental to the economic performance of firms in the Copenhagen area in Denmark, and Östbring and Lindgren (2013) found unrelated skill inflow to positively impact productivity in capital-intensive industries. These divergent findings imply that knowledge and abilities are contextual, and we need to further improve our conceptualization and operationalization of knowledge and ability and their role in different sectors and firms. We theorize that relatedness in the cognitive dimension can be achieved through several means. By combining multiple forms of knowledge, it is also likely that both short and long distances in the cognitive dimension may be fruitful for learning. The more detailed accounts we are able to give of individual agents' formalized knowledge *and* experiences, and the collected variety of those abilities within the firm, the more accurately will we be able to determine the effects of variety on firm performance.

Research Design

The choice of knowledge intensive business services (KIBS) for our study is due to the role of knowledge and learning in those industries. In comparison to capital-intensive sectors, which rely on physical capital for their performance (Östbring & Lindgren 2013), firms in KIBS depend on their ability to learn and apply knowledge for their performance. KIBS are mainly engaged in research or consultancy activities, ranging from advertising, patenting and IT consultancy to research in biotech or forestry. These firms often show a high degree of specialization. Their ability to learn and adapt is their competitive advantage, and employees' knowledge and learning are directly connected to outputs and performance (Hine et al. 2013). The client and research focus of these industries imply that firms have a focus of change – they try to adapt and evolve in accordance with existing research and potential client needs – and there is likely a low prevalence of routine tasks. This suggests that KIBS are imbued with a great deal of dynamism, which thrives on knowledge exchange and learning. Thus, by using KIBS in our study, we hope to isolate the effects of different forms of knowledge on workplace performance in these sectors.

Data and sampling

We base our analysis on longitudinal matched employee-employer data from the database Astrid at the Department of Geography and Economic History at Umeå University. The database holds yearly information on all individuals, firms and plants (workplaces) in Sweden. For the purpose of the paper, knowledge-intensive business services (KIBS) with 10 employees or more in Sweden are selected[1]. They are observed over the period 2000-2010. The time period 2000-2010 is chosen to maximize the dataset and still be able to create a 15-year backlog (i.e., for employees in KIBS in 2000 we go back to

[1] In small plants (<10 employees), employees are likely to have different work tasks and roles, and learning occurs between employees and external agents rather than between employees.

1985 to determine where and with whom they have previously worked). KIBS are defined by their standard industrial classification code (SIC-code). We use the Swedish five-digit code, SNI02, to select all firms with codes between 72100 and 74409.

In the initial sample, there were 5,273 plants in 2000 and 9,207 in 2010: the number of individuals employed at these plants almost doubled during the period, from 196,890 to 373,466. But due to missing data on one or several key variables, the final sample was reduced. There are 1,736 unique plants in the sample of which 1,187 are single-plant firms and 549 are plants that belong to multi-plant firms. This gives a total of 5,517 observations in the single-plant firm analysis and 3,226 observations in the multi-plant firm analysis due to the unbalanced panel structure. The total number of employees in the total sample increases from 29,713 in 2000 to 37,215 in 2010, and the median number of employees at a plant is 35. In these relatively small plants it is reasonable to assume that most employees interact with one another to some extent, even though the intensity of the interactions probably varies. There is a small majority of men working in the concerned industries; roughly 60 percent of all employees are men throughout the period. There is also an overall increase in the human capital ratio (ratio of employees with a bachelor's degree or higher) in the industries in our sample over the period (about 10 percent).

Dependent variable

The dependent variable is labor productivity, measured as value added per employee per workplace for each year between 2000 and 2010. Labor productivity measures the relative efficiency of a plant or firm and is not as straightforward a measure of learning and innovation as patents are. But the use of patents in analyses of learning and innovative behaviors excludes parts of the economy from analysis (e.g., KIBS), and this exclusion is avoided when labor productivity is used as the dependent variable. Moreover, Schumpeter (1939) argued that innovative firms use their resources more efficiently than their less innovative competitors do. Thus, labor productivity is a suitable measure of innovative behavior, while simultaneously being the most straightforward measure of industrial output (Rigby and Essletzbichler 2006).

The database only holds information on value added for firms, so for firms with more than one plant, value added is allocated according to the wage quota of the plant (as done by Boschma et al. 2009). Value added is then calculated as a per capita measure of productivity. In an attempt to verify the appropriateness of the allocation of value added between plants belonging to the same firm, it is also allocated in accordance with share of firm employment (as done by Martin et al. 2011). This is viewed as a more egalitarian way of allocating productivity, as every employee is then valued as being equally important to productivity. There was an insignificant difference in the value added allocated to the plants using the two different methods. This is most likely due to small wage differences between plants in the same firm in KIBS. Whereas a manufacturing firm will have different functions for its plants, e.g. R&D and production, a KIBS firm will have approximately the same competences in its plants, and the reason for having multiple plants is to be accessible to multiple markets, thus the wages do not vary as much between plants as they may do in multi-plant manufacturing firms. Regional wage differences in KIBS in Sweden are also relatively small as compared to international differences.

Independent variables

As described previously, the aim of the present paper is to include varieties of worker experience (skills) to the discussion of the effects of varieties of formal education (knowledge) on plant performance. Therefore there are four sets of independent variables that are entered into the model in consecutive steps. Initially, an indicator of human capital (HumCap) is calculated as the relative frequency of employees with a bachelor's degree or higher to reflect whether it is the concentration of human capital per se that is of importance. Traditionally, a high human capital ratio is presumed to be beneficial to plant performance because higher education signals high generic ability in information processing and motivation (Becker 1962; Card 1999; De la Fuente and Ciccone 2003; Olneck 1979). Then the effects of variety in formal education (knowledge) on productivity are estimated. Entropy measures, proposed by Frenken et al. (2007) and used by Boscham et al. (2009) and Östbring and Lindgren (2013), of relatedness of formal knowledge are calculated from a three-digit educational variable in the database, which describes the main subject of each individual. The three-digit level is the most detailed category and contains information about the specific subject, while the two-digit category amalgamates the subjects into fields of knowledge. The one-digit level is a broad umbrella category, not completely different from university faculties and contains the greatest variety within its levels.

The third set of independent variables concerns a variety of industry experiences (applied knowledge) within the labor force at the plant. Using a 15-year backlog for each current employee, their past workplaces and the industry of those workplaces are recorded and pooled to create a variety of industry experiences within the workplace. Using a four-digit sector code (SNI02), the variety of industry experiences of the employees at the workplace is estimated. Similar to the educational variable, the industry code can be disaggregated such that the four-digit code is the most detailed and individuals who have worked in the same four-digit industry are perceived to be similar in that aspect of experience. Individuals who have experience in the same three-digit code but different four-digit codes are regarded as having related industry experience and individuals who do not share either a four-digit or a three-digit code are unrelated in their industry experiences. Entropy measures of the pooled experiences in different industries are calculated using the same equations as for the educational variety.

The fourth set of independent variables is a variety of previous knowledge interactions that the current employees at the plants have experienced. As for the industry experience variables, each employee is traced 15 years back in time. The objective is to find all of the individuals with whom the specific employee has worked and thus all of the formal education (knowledge) that the individual has come across and may have been influenced by in an applied setting. All past interactions (three-digit educational categories) of all employees at the plant are pooled to create a variety of knowledge exposure. From this pool, entropy measures of the similarity, relatedness and unrelatedness of knowledge exposure in the workforce are estimated.

The same entropy equations are used for the three sets of independent variables. For the in-house formal education variables and for the knowledge exposure variables, the same three-digit education variable is used. For the applied knowledge exposure variables (industry experience), the sector code variable (SNI92 and SNI02) is the foundation. The degree of similarity (SIM) in any of the three variables (employee formal knowledge (SIM), industry experience (IND_SIM) and knowledge exposure (EDU_SIM)) is calculated for each plant as the inverted entropy at the most detailed level of analysis (three-digit category for education and four-digit category for industry). In the equation, p_i^{III} is the share of three-digit educational category *i* or four-digit sector category *i* and N^{III} is the number of categories within a plant (1).

$$\text{SIM, IND\_SIM, EDU\_SIM} = \frac{1}{\sum_{i=1}^{NIII} p_i^{III} \log_2\left(\frac{1}{p_i^{III}}\right)} \tag{1}$$

The larger the value, the more similar the formal in-house competences, the industry experiences and the knowledge exposure, respectively, of all employees within a plant. The similarity variables (SIM, IND_SIM, EDU_SIM) were transformed according to ln(x+1) due to the skewness of the variables and the high occurrence of zeros. The degree of relatedness in the three variables is the shares of two-digit educational categories and three-digit sector code categories, p_j^{II} (3), when accounting for the occurrences of the more detailed categories within these categories (2). H_j can be considered a weight that controls for the degree of similarity within a two-/three-digit category (4). The weight lowers the relatedness score of a high share of a two-digit category that simultaneously contains a high share of a three/four-digit category and thus is similar rather than related.

$$\text{REL, IND\_REL, EDU\_REL} = \sum_{j=1}^{N^{II}} p_j^{II} H_j \tag{2}$$

where;

$$p_j^{II} = \sum_{i \in S_j^{II}} p_i^{III} \tag{3}$$

and;

$$H_j = \sum_{i \in S_j^{II}} \frac{p_i^{III}}{p_j^{II}} \log_2\left(\frac{1}{p_i^{III} / p_j^{II}}\right) \tag{4}$$

High occurrence of relatedness in formal education or experience of any of the two sorts will generate high values in the relatedness variables. The degree of unrelatedness in any of the abilities variables is measured as the summed shares of one-digit categories, p_i^I, weighed by their individual logged inverse values (5). The larger the value, the more unrelated the in-house competences.

$$\text{UNREL, IND\_UNREL, EDU\_UNREL} = \sum_{l=1}^{N^1} p_l^I \log_2\left(\frac{1}{p_l^I}\right) \qquad (5)$$

In addition to the entropy measures of knowledge variety, centered interaction variables are constructed. The first set of interaction variables gives the conditional effect of human capital ratio and each of the entropy measures, whereas the second set of interaction variables establishes the conditional effect of formal knowledge variety and the two different types of experience variety. By so doing, we determine whether the effects of different knowledge constellations are additive or conditional (multiplicative). We regard this as testing whether the effects of different forms of knowledge on plant performance are unaffected by the occurrence of other forms of cognitive abilities or whether there is an overlap effect. The overlap effect may either abate or promote the effect of knowledge relatedness in one type of knowledge. *A positive overlap effect* is defined as enhancing the initial effect of the other included variable in the interaction term (i.e., a negative effect of one variable on the dependent variable is amplified by high values in the other variable), whereas *a negative overlap effect* occurs when the initial effect is abated or even reversed by high values in the other variable. Knowledge forms that only have additive effects on plant performance and no significant interaction terms are regarded as independent. In instances where a knowledge variable has the same type of effect (positive/negative) on plant performance as another independent knowledge variable, their effects are indicative of substitution. That refers to a scenario in which one independent variable can be substituted by another to achieve the same effect on plant performance. For the significant interaction terms, graphs show how the effect of one knowledge variable is altered at three different levels in the other knowledge variable (low, average and maximum values).

Control variables

As discussed previously, there are factors in the regional environment that may affect the performance of plants. This is especially true for single-plant firms, Rigby and Brown (2015) found that single-plant firms rely on the local supply of labor for their performance whereas multi-plant firms are more dependent on their extensive supplier-buyer networks for their performance. There are four variables that account for different potential agglomeration effects. Regional diversity (Reg_Div) is calculated as the variety of industries (four-digit sector code) in the region. This variable represents the existence of Jacob's externalities, which theoretically promote learning through the potentially numerous interactions of various forms of knowledge. However, most previous empirical studies on the effects of diversity have failed to find conclusive results on its benefits (e.g., Neffke et al. 2012). The variable "Urbanization" is a measure of the absolute size of the region (total number of plants in the region). Urbanization externalities may arise from access to infrastructure and a large market and labor market, but this kind of agglomeration is also associated with congestion and high land rents. Therefore, it is expected to negatively impact plant performance. Industry relatedness (Ind_Div) represents potential externalities associated with agglomerations of related industries and is the share of plants in the same two-digit sector category as the plant under study. We particularly expect single-plant firms in regions with high industry relatedness to be exposed to numerous learning opportunities, which positively impacts plant performance (see, e.g., Boschma and Iammarino (2009) and Frenken et al. (2007) on the positive effects of a related regional industry setup). MAR externalities, i.e. benefits arising from the co-location of firms in the same sector, are accounted for by the variable "Specialization". This variable is calculated as the regional relative frequency of plants in the same industry as the plant under study. All in all, we expect single-plant firms to exhibit a greater dependence on the local environment than multi-plant firms, which depend more heavily on management decisions, restructuring and widespread buyer-supplier networks (Hakkala 2006; Rigby and Brown 2015).

There are also a few variables concerned with the characteristics of plants that may affect labor productivity. Because the in-house abilities are under scrutiny, trust and experience are believed to be key features in introducing more far-fetched ideas and applying them (March 2010), thus the average worker age (Worker_Age) is presumed to positively impact productivity. The higher the average age, the more likely it is that employees have worked together for some time and learned to communicate with and trust each other. We expect plant size to positively influence productivity at the plant, but because plant size is part of the dependent variable (per capita productivity) it is excluded from the model to avoid simultaneity. An increase in the number of employees at a plant may temporarily reduce labor productivity during a period of absorption and integration of the new employee'(s') knowledge. (Plant_growth) is thus expected to negatively impact labor productivity. Urbanization was transformed using its natural logarithm due to skewness in the variables. Industry diversity was transformed according to *ln(x+1),* due to high occurrence of zeros in the initial sample.

The model

The present study focuses on in-house skills, various forms of cognitive abilities and their independent and combined effects on plant performance. To test whether past worker experiences can contribute to creating a dynamic environment for learning *and* innovation, pooled OLS models are estimated in STATA for single-plant firms and multi-plant firms respectively. All models are weighted by plant size and cluster robust standard errors are used. There is a high occurrence of small plants in the samples, but the largest plants (the top ten percent) employ 42 percent of all individuals. By using weights in the models, the large plants will be ascribed a larger portion of the explained variance. There is potentially unobserved heterogeneity associated with the different plants, and this affects their performance. To abate the risks of idiosyncratic traits blurring the effects of our independent variables, dummy variables are used to represent region, industry and year. The geographic location of the plant is controlled for by using dummy variables for 53 (54-1) functional analytical regions determined by the Swedish Agency for Economic and Regional Growth (Tillväxtverket). The industry dummies are based on the 26 (27-1) five-digit SIC-codes (SNI02) associated with the firms. The first lag of all skill variables (*t-1*) is used in the models, because knowledge and learning need to be applied to generate economic value in a plant. Thus the realizations of knowledge advancements are not instantaneous but slightly delayed. Because in-house abilities are under scrutiny, we regard deeper lags as unnecessary due to employees' existing familiarity with and understanding of other employees' knowledge and skills. The other explanatory variables and the dependent variable are measured at time *t*.

- Table 1 around here –

Empirical results

Table 2 presents the results on the additive and conditional effects of different forms of knowledge variety on plant performance in single-plant firms, when accounting for the human capital ratio present at the plant. Model 1A, 2A and 3A (Table 2) present the additive effects, whereas Model 1B, 2B and 3B present the interaction terms (conditional effects) for human capital ratio and the entropy measures of knowledge and experience variety. The correlations between the different forms of cognitive proximity were tested to verify that they are measurements of different sets of cognitive abilities and not just different representations of the same ability, and no severe collinearity was found. As expected, our results show that a high concentration of human capital positively impacts plant performance (Model 1A, 2A and 3A). This is in accordance with our expectations, given the knowledge-intensive work tasks that characterize these types of industries.

Table 2 about here

Only related formal knowledge is significant, showing a positive relationship, when controlling for the human capital ratio. The positive effect of related knowledge is in line with the literature (e.g. Boschma et al 2009) and expected due to the strong dependence on learning for plant performance in KIBS. KIBS are permeated with a great deal of specialization and their change focus requires efficient communication and learning, something that is made easier with high degrees of relatedness in the in-house portfolio. But, if we turn to Model 1B and the presumed overlap effects (characterized by the interaction terms) between human capital ratio and knowledge variety, it is shown that a high human capital ratio can abate the negative effect of high levels of similarity and unrelatedness in the in-house knowledge portfolio (Table 2, Model 1B). Together with high human capital ratios, high levels of similarity or unrelatedness have positive impacts on plant performance (Figure 1, Graph 1a and 1b). The significant interaction terms between human capital ratio and similarity and unrelatedness in formal knowledge, indicate conditional overlap effects between these forms of knowledge.

Figure 1 about here

We identify the two overlap effects between human capital and similarity and human capital and unrelatedness in formal knowledge to be *negative overlap effects*. This means that an increase in one of the variables abates the initial effect of the other variable regardless of whether that effect is positive or negative.

In Model 2A and 2B (Table 2), the effects of the variety of industry experience are addressed in combination with the effects of human capital ratio in single-plant firms. Industry experience represents an applied form of knowledge variety, which presumably has the same effects as formal knowledge variety on plant performance. In the additive model (Model 2A), human capital ratio and high levels of related industry experiences positively impact plant performance, whereas unrelatedness in industry experience negatively impacts plant performance. These results are in line with our expectations, as high generic abilities in communication, problem solving and learning are assumed to be beneficial to all industries and plants. Also, an in-house staff with work experiences in a related variety of industries will be able to communicate efficiently and learn from each other. In contrast, a high degree of unrelated knowledge, irrespective of whether it is theoretical or applied, will complicate learning due to the lack of mutual knowledge. Similarity in industry experience have no significant impact on plant performance in the additive model, when controlling for the human capital ratio. In the conditional model (Model 2B), there is no significant interaction between industry unrelatedness and human capital ratio, indicating that the observed negative effect of industry unrelatedness in the additive model (Model 2A) is an independent effect, unaffected by the human capital ratio at the plant. There is a positive interaction term between industry relatedness and the human capital ratio that translates into a positive overlap effect (see Figure 1, Graph 2a). The positive impact of relatedness in industry experience on plant performance is further heightened at high human capital ratios. Related applied knowledge is more specialized than related theoretical (formal) knowledge (Howells 2012) and at higher levels of human capital, related industry knowledge can be even more efficiently communicated and transformed into productive practice.

When we explicitly address the past formal knowledge exposure of the current workers in Model 3A, all knowledge variables are significant. The additive model (3A) shows strong positive effects of both high levels of related knowledge exposure and human capital ratio, whereas high levels of similarity and unrelatedness in knowledge exposure negatively impact plant performance. These findings are in line with the current empirical and theoretical literature on learning and innovation (Boschma et al. 2009).

By comparing Model 1A and 3A we find that the effects of past knowledge exposure are spread throughout the variety spectrum, whereas only related formal knowledge impacts plant performance. This indicates that there is a socializing aspect to knowledge that is important in KIBS; the overall effect of the variety of experiences in knowledge interactions is greater than the effect of the variety of formal knowledge. This knowledge has been shared in an applied setting under specific social and organizational circumstances. Therefore it may also be associated with a social and organizational experience that does not exist in the formal knowledge accounted for by the employees' own educational backgrounds. The knowledge exposure variables represent theoretical (formal) knowledge that the individuals have encountered in their professional life. It is highly likely that this form of knowledge also has characteristics that resemble applied knowledge, and the potential benefits, under the right circumstances, are larger than those associated with the educational background. There is potentially greater variety in the knowledge exposure variable in total than there is in the formal knowledge variable. There are no conditional effects between past knowledge exposure and human capital ratio in single-plant firms, indicating that the effects are independent of the level of human capital. With regard to the control variables, the two variables that represent plant characteristics, average worker age and plant growth, are significant. Higher average worker age positively impacts plant performance, presumably due to the longer work experiences and the deepened trust that will have built up over time. Plant growth has a negative impact on performance, most likely due to the construction of the per capita measure of plant performance. Two of the four variables that represent the regional industry setup are significant, the industry diversity variable and the regional diversity variable. A related industry base positively impacts the performance of single-plant firms whereas regional diversity negatively impacts plant performance. This is in line with contemporary studies on agglomeration externalities (e.g., Neffke et al. 2011; 2012) showing both higher survival rates and productivity for plants in regions with a related industry base rather than a diversified one. The insignificant effect of urbanization and specialization economies further strengthens current theories on the role of relatedness in promoting learning and innovativeness. Firms in specialized regions run a greater risk of lock-in and slower rates of innovation, whereas firms in urbanized areas may suffer from the negative aspects of urbanization, such as congestion and high rents, etc. The regional relatedness variable is also insignificant, which presumably is a trait specific to the industries in KIBS. Because of the highly specialized character of the activities carried out by most firms in KIBS, the cognitive distance between firms in apparently related industries (as implied by their SIC-code) may be too great for productive knowledge spillovers to occur.

-Table 3 about here –

In Table 3 we show the results on the additive and conditional effects of different forms of knowledge variety on plant performance in multi-plant firms, when accounting for the human capital ratio present at the plant. Model 1C reveals that high levels of similar and unrelated formal knowledge is harmful to plant performance, whereas a high human capital ratio positively impacts plant performance in multi-plant firms. In models 1D and 3D we identify the conditional effects of relatedness when accounting for the level of human capital to be *negative overlap effects*. The higher the level of relatedness in formal knowledge and past knowledge exposure, the less positive the effect of human capital ratio at the plant. When the human capital ratio approaches 1, the conditional effect of relatedness is harmful to plant performance (see Figure 2, Graph 1c and 3d). This may be due to the multi-plant structure of these firms. High levels of human capital eases communication and information transfer within and between the plants, whereas high levels of relatedness in one plant may represent a different kind of relatedness or specialization than what is present in the other plants within the firm. The inter-plant communication may thus be obstructed by high levels of relatedness in on plant. The lack of significance for the interaction terms for similarity and unrelatedness indicate that the negative impacts registered in model 1C are independent of the level of human capital at the plant. Model 2C shows no significant results for staff industry experience in multi-plant firms when controlling for human capital ratio. When checking for conditional effects (model 2D) we find that high levels of human capital can reduce and even turn the negative impact of high levels of similarity in industry experience to a positive influence on plant performance (Figure 2, Graph 2c).

-Figure 2 about here-

Model 3C presents a negative relationship between high levels of unrelated past knowledge exposures and plant performance. As expected individuals with heterogeneous past work interactions and professional networks will have developed in different directions and thus have difficulties to communicate and learn efficiently. In model 3D the conditional effects of knowledge exposure and human capital ratios are displayed. As in the case with industry experience in multi-plant firms, the negative impact of high levels of similarity in knowledge exposure are mitigated by high human capital levels (Figure 2, Graph 3c). At human capital ratios close to one, the positive impact of human capital in unaffected by the level of similarity in the staff.

A comparison of Table 2 and Table 3 indicate that there are fewer benefits arising from agglomeration externalities for multi-plant firms than for single-plant firms. Rigby and Brown (2015) found multi-plant firms to benefit from their extensive buyer-supplier networks rather than agglomeration externalities associated with access to specialized labor markets. In a different study, Hakkala (2006) explained the higher productivity of multi-plant firms to depend mainly on an organizational and structural flexibility that allowed firms to invest in new productive plants and divest in low productive plants, thus changing their overall productivity.

-Table 4 about here-

Table 4 presents the relative and conditional effects of formal knowledge composition on plant performance when accounting for the experience variety present in single-plant firms. In Model 4A, the additive effects of formal knowledge and past industry experience on plant performance are estimated and displayed. Similar to Model 1A and 2A, relatedness in formal knowledge and industry experience continues to positively impact plant performance. This is in line with theories of complementary knowledge and implies that when the in-house staff has previous experiences from related industries or related formal knowledge they can promote each other's knowledge further. Whereas the previously found effect of formal knowledge relatedness on plant performance was independent of the level of human capital at the plant (Table 2, Model 1B), it is found to be conditioned by the level of relatedness in industry experience, and vice versa, at the plant (Model 4B). High levels of industry relatedness has a stronger positive impact on plant performance if there is also high levels of relatedness in formal knowledge at the plant (Figure3, Graph 4b). Furthermore, unrelatedness in both formal knowledge and industry experience has a negative impact on plant performance in single-plant firms. This is presumably due to lengthy learning processes and delayed knowledge application. The negative impact is reinforced if there are high levels of unrelatedness in both formal knowledge and industry experience, creating an even larger communication gap between the employees (Figure 3, Graph 4c). This is in accordance with existing literature on proximity dimensions (see, e.g., Boschma 2005) claiming that unrelatedness (long distances) in multiple dimensions may contribute to an inability to communicate and thus to learn and innovate. Models 4A and 4B also reveal that the negative impact of knowledge similarity is a purely conditional effect where the influence is determined by the level of similarity in industry experience (Figure 3, Graph 4a).

-Figure 3 about here-

Model 5A displays the impact of past knowledge exposure when controlling for the formal knowledge variety present in single-plant firms. High levels of similarity and unrelatedness in knowledge exposure negatively impacts plant performance, which is in line with theories of proximity dynamics and learning (Nooteboom 2009; Nooteboom et al. 2007). The positive impact of relatedness in formal knowledge that was recorded in Models 1A and 4A remains when the other knowledge variable, controlled for, is knowledge exposure. In Model 4B the positive effect of related formal knowledge increases with high levels of relatedness in industry experience whereas in the case of human capital and knowledge exposure the effects of relatedness in formal knowledge are independent of the other knowledge variable. Thus, relatedness in formal knowledge contributes to plant productivity, presumably through the high learning and innovative potential, in single-plant firms. In these plants, the in-house knowledge constitutes the entire knowledge pool from which to extract, recombine and apply knowledge. In Model 5B (Table 4) we see a negative overlap effect where high levels of similarity in formal knowledge *and* past knowledge exposure generate conditional effects that are beneficial to plant productivity (Figure 3, Graph 5a). This can be explained by high levels of specialization at a plant, which generates diversification through new services and products. Timmermans and Boschma (2013) found similar labor flows to be the most influential for plant performance in the Copenhagen region and suggested a hidden diversification in dense markets with intensive competition. For example a law firm will have staff with highly similar formal knowledge and a majority of its employees will have been exposed to similar forms of knowledge at their previous workplaces due to the specialized form of knowledge that they have, which attracts them to specific workplaces.

Table 5 displays the impact of formal knowledge variety and experience variety on plant performance in multi-plant firms. In contrast to Model 1C, Model 4C reveals that related past industry experience has a significant positive effect on plant performance when controlling for formal knowledge variety. Related industry experience had no impact on plant performance when controlling for the human capital ratio. Moreover, unrelatedness in formal knowledge negatively impacts plant performance, and in comparison with the conditional model (4D), it can be determined that the effect is independent of occurrences of unrelated industry experience. In contrast, the level of similarity in past industry experiences conditions the effect of similarity in formal knowledge on plant performance (Model 4D).

-Table 5 about here-

Model 4D shows a positive interaction effect between similarity in formal knowledge and similarity in past industry experiences. This positive interaction translates into a negative overlap effect that is displayed in Figure 4 (Graph 4d) where high levels of similarity in industry experience substantially reduce the negative effect of similarity in formal knowledge, to the extent where high levels in both variables generate a positive effect on plant performance. As discussed previously this is most likely due to a hidden diversification in specialized firms in dense markets. Model 5C demonstrates a negative impact of unrelated formal knowledge that has persisted throughout the additive multi-plant models. It is also shown that the variety in past knowledge exposure has no impact on plant performance when controlling for formal knowledge variety. There is, however, a conditional effect similar to the one between similar formal knowledge and similar industry experience. High levels of similarity in both formal knowledge and past knowledge exposure generate a variety through which similarity in two sub-dimensions of cognitive proximity enable deepened specialization (Figure 4, Graph 5c).

- Figure 4 about here -

Concluding remarks

The aim of the present paper was to help increase our understanding of cognitive distance and its effects on firm performance. In particular, we focused on the need to elaborate on the meaning of cognitive distance, as it is commonly perceived in the literature. The idea proposed in most empirical studies – that cognitive distance is more or less equivalent to formal education – was challenged by suggesting some alternative definitions that find support in evolutionary economic geography and other fields of theoretical discussion. We have distinguished between different types of cognitive relatedness and their independent and overlapping effects on productivity in single-plant and multi-plant firms respectively. By viewing the cognitive dimension as a way of relating abilities to one another, we have distinguished between formal knowledge, industry experience and past knowledge exposure. We have been able to show that the cognitive abilities of individuals are multi-faceted and strongly linked to past experiences. Furthermore, it has been suggested that the influence of labor force knowledge and knowledge variety differ in single-plant and multi-plant firms. To some extent formal education is a crude measure of the cognitive capacities of individuals, because it is a snapshot and usually measured during the beginning of adulthood. The formation of individuals' knowledge, skills and experiences, or differently put their professional identity, is an ongoing process that is more effectively taken into account by drawing on information from the past. The historical records of professional life may be very helpful when portraying the individual and his/her job-related capacities. Differences between individuals with the same formal education stand out more clearly when allowing for their historical life trajectories and the varying knowledge and skills they have been exposed to throughout time.

The professional histories of individuals may also be important for estimating cognitive distance in a more thorough way. When incorporating the stories told by the life paths, individuals with the same formal education may actually be very similar or very different. The same applies to individuals with different formal education – they may be very different, but they may also be much more alike than type of education and education level would seem to indicate. This might be one contributory factor to the inconsistent results on cognitive distance between workers that have been reported in the literature (e.g., Boschma et al. 2009; Timmermans and Boschma 2013; Östbring and Lindgren 2013). In line with the above discussion, the results of our empirical analyses suggest that past knowledge experiences and formal education offer multiple channels for knowledge integration at the workplace and that the specific labor force knowledge characteristics present at a plant condition learning. It has been further shown that the organizational structure and flexibility associated with single-plant and multi-plant firms, respectively, generate different plant performance outcomes of knowledge variety. In single-plant firms, in KIBS, human capital, knowledge and experience variety has a great deal of explanatory power with regard to explaining variations in firm performance. In multi-plant firms, on the other hand, high levels of human capital positively influence plant performance, presumably due to the need for communication and application of administrative decisions made externally.

Our results also show that different types of cognitive proximities may interact by weakening or reinforcing the effects on firm performance. For example, in the literature it is commonly reported that cognitive similarity is detrimental to firm performance due to lock-in effects and inertia. However, we find that negative effects of similarity in formal education may be reduced (and sometimes even reversed to a positive effect) by high levels of similarity in historical knowledge exposure. This result could be interpreted as an indication of hidden diversification where, for example, long-term experience of fellow workers in highly qualified professional jobs (e.g. lawyers, physicians, engineers, etc.) makes it possible to successfully diversify economic activities into new activities that appear to be the same in the register data. Our results also reveal that there is a link between human capital and different degrees of cognitive relatedness. The commonly found negative effects of similar formal knowledge may be balanced by high levels of human capital in terms of high education. The argument put forward by Boschma et al. (2009) that strong firm productivity is not due to human capital concentrations *per se* but to cognitive relatedness among employees, may be refined by recognizing the reciprocity between these two factors. Similarity in terms of cognitive relatedness apparently has different implications if the staff have short or long education experiences. Longer and more extensive education makes it more likely that individuals have been exposed to broader sets of perspectives and different ways of thinking, which give rise to hidden diversity. Formal cognitive similarity in the group of highly educated people may therefore conceal aspects of related variety beneficial to firm performance.

In most studies on labor force knowledge and its effects on plant performance, the focus is on labor mobility and the relationship between formal cognitive relatedness and geographic proximity. In the present study, however, the aim has been to examine the impact of cognitive distances in the in-house competence portfolio on plant performance. Furthermore, it has been argued that cognitive relatedness can be achieved and estimated in more than one way. Our results show that there is more than one way to determine cognitive proximity, and the cognitive dimension is only one of several dimensions. Therefore, we conclude that theories of the workings of proximity dimensions are underdeveloped and offer promising avenues for future research.

References

Almeida P, Kogut B (1999) Localization of knowledge and the mobility of engineers in regional networks. *Management Science* 45:905–917.

Amin A, Cohendet P (2005) Geographies of knowledge formations in firms. *Industry and Innovation* 12:465-486.

Balland P-A, De Vaan M, Boschma R (2013) The dynamics of interfirm networks along the industry life cycle: The case of the global video game industry, 1987-2007. *Journal of Economic Geography* 13:741-765.

Bathelt H, Glückler J (2005) Resources in economic geography: from substantive concepts towards a relational perspective. *Environment and Planning A* 37:1545-1563.

Bathelt H, Glückler J (2013) Institutional change in economic geography. *Progress in Human Geography*, Online First Version of Record - Oct 18, 2013:1-24.

Becker G (1962) Investment in human capital: a theoretical analysis. *Journal of Political Economy* 70:9-49.

Becker MC (2004) Organizational routines: A review of the literature. *Industrial and Corporate Change* 13:643-677.

Boschma R (2005) Proximity and Innovation: A Critical Assessment. *Regional Studies* 39:61-74.

Boschma R, Eriksson R, Lindgren U (2009) How does labor mobility affect the performance of plants? The importance of relatedness and geographical proximity. *Journal of Economic Geography* 9:169-90.

Boschma R, Eriksson R, Lindgren U (2014) Labour market externalities and regional growth in Sweden: The importance of labour mobility between skill-related industries. *Regional Studies*, DOI: 10.1080/00343404.2013.867429.

Boschma R, Iammarino S (2009) Related variety, trade linkages and regional growth in Italy. *Economic geography* 85:289-311.

Boschma R, Minondo A, Navarro M (2012) The emergence of new industries at the regional level in Spain: A proximity approach based on product relatedness. *Economic Geography* 89:29-51.

Breschi S, Lissoni F (2009) Mobility of skilled workers and co-invention networks: an anatomy of localized knowledge flows. *Journal of Economic Geography* 9:439–468.

Card D (1999) The causal effect of education on earnings, in: O. Ashenfelter and D. Card (eds). *Handbook of labor economics, vol 3A*, Amsterdam: Elsevier Science, pp. 1801-1863.

Cohen WM, Levinthal DA (1990) Absorptive capacity: a new perspective on learning and innovation. *Administrative Science Quarterly* 35:128–152.

De la Fuente A, Ciccone A (2003) *Human capital in a global and knowledge-based economy – final report*. European Commission, Luxembourg. p 3-32.

Eriksson R (2011) Localized spillovers and knowledge flows: How does proximity influence the performance of plants? *Economic Geography* 87:127-52.

Eriksson R, Lindgren U (2009) Localized mobility clusters: impacts of labour market externalities on firm performance. *Journal of Economic Geography* 9:33-53.

Farole T, Rodriguez-Pose A, Storper M (2010) Human geography and the institutions that underlie economic growth. *Progress in Human Geography* 35:58-80.

Frenken K, Van Oort F, Verburg T (2007) Related variety, unrelated variety and regional economic growth. *Regional Studies* 41:685–697.

Gertler M (2003) Tacit knowledge and the economic geography of context, or The undefinable tacitness of being (there). *Journal of Economic Geography* 3:75–99.

Grabher G, Ibert O (2014) Distance as asset? Knowledge collaboration in hybrid virtual communities. *Journal of Economic Geography* 14:97-123.

Granovetter M (1985) Economic action and social structure: the problem of embeddedness. *American Journal of Sociology* 91:481–510.

Grant RM (1996a) Prospering in dynamically-competitive environments: Organizational capability as knowledge integration. *Organization Science* 7:375-387.

Grant RM (1996b) Toward a knowledge-based theory of the firm. *Strategic Management Journal* 17:109-122.

Hakkala K (2006) Corporate restructuring and labor productivity growth. *Industrial and Corporate Change* 15:683-714.

Hansen T (2012) Substitution or overlap? The relations between geographical and non-spatial proximity dimensions in collaborative innovation projects, *Paper I* in: *The geography of the knowledge economy*. PhD thesis, Department of Geography and Geology, University of Copenhagen pp 81-109.

Harrison JS, Hitt MA, Hoskisson RE, Ireland RD (2001) Resource complementarity in business combinations: Extending the logic to organizational alliances. *Journal of Management* 27:679-690.

Heimeriks G, Boschma R (2013) The path- and place-dependent nature of scientific knowledge production in biotech 1986-2008. *Journal of Economic Geography*. Advance Access (doi:10.1093/jeg/lbs052). 1-26.

Hine D, Parker R, Pregelj L, Verreynne M-L (2013) Deconstructing and reconstructing the capability hierarchy. *Industrial and Corporate Change* (Advance Access doi:10.1093/icc/dtt046).

Howells J (2012) The geography of knowledge: never so close but never so far apart. *Journal of Economic Geography* 12:1003-1020.

Kogut B, Zander U (1992) Knowledge of the firm, combinative capabilities, and the replication of technology. *Organization Studies* 3:383-397.

Lacetera N, Cockburn IM, Henderson R (2004). Do firms change capabilities by hiring new people? A study of the adaption of science-based drug discovery. *Advances in Strategic Management* 21:133-159.

Lam A (1997) Embedded firms, embedded knowledge: Problems of collaboration and knowledge transfer in global cooperative ventures. *Organization Studies* 18:973-996.

Maliranta M, Mohnen P, Rouvinen P (2009) Is inter-firm labor mobility a channel of knowledge spillovers? Evidence from a linked employer–employee panel. *Industrial and Corporate Change* 18:1161–1191.

Maskell P (2001) The firm in economic geography. *Economic Geography* 77:329-344.

Maskell P, Malmberg A (1999) Localised learning and industrial competitiveness. *Cambridge Journal of Economics* 23:167-185.

March J (2010) *The ambiguities of experience*. Ithaca: Cornell University Press, 152 p.

Neffke F, Henning M, Boschma R, Lundquist K-J, Olander L-O (2011) The dynamics of agglomeration externalities along the life cycle of industries. *Regional Studies* 45:49-65.

Neffke F, Henning M, Boschma R (2012) The impact of aging and technological relatedness on agglomeration externalities: a survival analysis. *Journal of Economic Geography* 12:485-517.

Neffke F, Henning M (2013) Skill relatedness and firm diversification. *Strategic Management Journal* 34:297-316.

Nonaka I, Ryoko T, Akiya N (2000) A firm as a knowledge-creating entity: A new perspective on the theory of the firm. *Industrial and Corporate Change* 9:1-20.

Nooteboom B (1992) Towards a dynamic theory of transactions. *Journal of Evolutionary Economics* 2:281-299.

Nooteboom B (1999) Innovation and inter-firm linkages: New implications for policy. *Research Policy* 28:793-805.

Nooteboom B (2004) Governance and competence, how can they be combined?. *Cambridge Journal of Economics* 28:505-526.

Nooteboom B (2009) *A cognitive theory of the firm, learning, governance and dynamic capabilities*, Cheltenham: Edward Elgar, 280 p.

Nooteboom B, Van Haverbeke W, Duysters G, Gilsing D, van den Oord A (2007) Optimal cognitive distance and absorptive capacity. *Research Policy* 36:1016–1034.

Olneck M (1979) The effects of education, in: C. Jencks (ed) *Who gets ahead?*, New York: Basics books inc, pp. 159-190.

Orlikowski W (2002) Knowing in practice: Enacting a collective capability in distributed organizing. *Organization Science* 13:249-273.

Penrose E (1959) *The theory of the growth of the firm. Fourth edition*. Introduction by C. N. Pitelis (Reprint 2013) Oxford: Oxford University Press, 249 p.

Polanyi M (1966) The logic of tacit inference. *Philosophy* 41:1-18.

Rigby D, Brown W (2015) Who benefits from agglomeration? *Regional Studies* 49:28-43.

Rigby D, Essletzbichler J (2006) Technological variety, technological change and a geography of production techniques. *Journal of Economic Geography* 6:45–70.

Song J, Almeida P, Wu G (2003) Learning-by-Hiring: When is mobility more likely to facilitate interfirm knowledge transfer? *Management Science* 49:351-65.

Spender J-C (1992) Limits to learning from the West: How Western management advice may prove limited in eastern Europe. *International Executive* 34:389-410.

Strambach S (2010) Path dependence and path plasticity: the co-evolution of institutions and innovation in the German customized business software industry, in: R. Boschma and R. Martin (eds) *The handbook of evolutionary economic geography*, Cheltenham: Edward Elgar, pp. 406-431.

Szulanski G (1996) Exploring internal stickiness: Impediments to the transfer of best practice within the firm. *Strategic Management Journal* 17 (Winter Special Issue):27-43.

Tanriverdi H, Venkatraman N (2005) Knowledge relatedness and the performance of multibusiness firms. *Strategic Management Journal* 26:97-119.

Teece D (2007) Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28:1319–1350.

Timmermans B, Boschma R (2013) The effect of intra- and inter-regional labour mobility on plant performance in Denmark: the significance of related labour inflows. *Journal of Economic Geography (*Advance Access doi: 10.1093/jeg/lbs059)

Torre A, Gilly J-P (2000) On the analytical dimension of proximity dynamics. *Regional Studies* 34:169-180.

Wuyts S, Colombo MG, Dutta S, Nooteboom B (2005) Empirical tests of optimal cognitive distance. *Journal of Economic Behavior and Organization* 58:277-302.

Östbring L, Lindgren U (2013) Labor mobility and plant performance: On the (dis)similarity between labor- and capital-intensive sectors for knowledge diffusion and productivity. *Geografiska Annaler: Series B, Human Geography* 95:287-305.

Table 1. *Descriptive statistics for all variables.*

Variable	**Description**	**Mean**	**S.D.**	**Min**	**Max**
Productivity (ln)	Labor productivity	13,24	0,59	4,67	18,37
SIM (ln +1)	Degree of similarity of formal skills	0,36	0,13	0	2,40
REL	Degree of relatedness of formal skills	0,51	0,39	0	2,15
UNREL	Degree of unrelatedness of formal skills	1,47	0,66	0	2,97
IND_SIM(ln +1)	Degree of similarity of industry experience	0,24	0,13	0	1,68
IND_REL	Degree of relatedness of industry experience	0,27	0,23	0	1,27
IND_UNREL	Degree of unrelatedness of industry experience	1,91	0,72	0	3,12
EDU_SIM (ln +1)	Degree of similarity of knowledge exposure	0,22	0,09	0	0,80
EDU_REL	Degree of relatedness of knowledge exposure	0,81	0,43	0	1,99
EDU_UNREL	Degree of unrelatedness of knowledge exposure	1,57	0,73	0	2,93
HumCap	Share of employees with bachelor's degree or higher	0,45	0,26	0	1
Worker_Age	Average worker age	40,77	5,52	21,60	63,64
Plant_growth	Change in number of employees between t & (t-1)	0,47	9,56	-127	161
Specialization	Share of similar industries in region	0,02	0,01	0	0,05
Urbanization (ln)	Total number of plants in region	8,78	1,31	4,01	10,12
Ind_Div (ln+1)	Variety of related industries	0,08	0,13	0	0,69
Reg_Div	Regional diversity of industries	0,17	0,18	0	1

Table 2. Additive and multiplicative weighted, pooled OLS estimations with cluster robust standard errors of the effects of human capital on plant performance in combination with different forms of variety of knowledge in single-plant firms in KIBS between 2000 and 2010 in Sweden.

	Model 1A		Model 1B		Model 2A		Model 2B		Model 3A		Model 3B	
Productivity (log)	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
HumCap (t-1)	.429***	.055	-.189	.274	.455***	.056	.372***	.085	.430***	.056	.438***	.077
SIM (log +1)(t-1)	-.077	.134	-.655***	.241								
REL(t-1)	.131***	.037	.188***	.062								
UNREL(t-1)	-.005	.032	-.129**	.056								
*HumCap * SIM*			.934**	.371								
*HumCap * REL*			-.152	.121								
*HumCap * UNREL*			.227**	.095								
IND_SIM(log +1)(t-1)					-.025	.069	.078	.122				
IND_REL(t-1)					.182***	.057	-.143	.124				
IND_UNREL(t-1)					-.046**	.021	-.038	.029				
*HumCap * IND_SIM*							-.243	.299				
*HumCap * IND_REL*							.677***	.225				
*HumCap * IND_UNREL*							-.016	.039				
EDU_SIM (log +1)(t-1)									-.917***	.316	-.839**	.369
EDU_REL(t-1)									.093*	.049	.085	.071
EDU_UNREL(t-1)									-.077**	.038	-.081*	.044
*HumCap * EDU_SIM*											-.148	.365
*HumCap * EDU_REL*											.017	.108
*HumCap * EDU_UNREL*											.009	.058
Worker_Age	.015***	.002	.014***	.002	.014***	.003	.014***	.003	.012***	.003	.012***	.003
Plant_growth	-.004***	.001	-.004***	.001	-.004***	.001	-.004***	.001	-.004***	.001	-.004***	.001
Specialization	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Urbanization (ln)	-.076	.423	-.135	.425	.030	.430	.029	.424	-.001	.426	-.008	.426
Ind_Div (ln+1)(t-1)	.614	.379	.664*	.381	.734*	.378	.741**	.374	.658*	.377	.658*	.376
Reg_Div	-.461**	.230	-.492**	.231	-.513**	.230	-.511**	.227	-.498**	.229	-.497**	.228
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	5517		5517		5517		5517		5517		5517	
Plants	1187		1187		1187		1187		1187		1187	
R^2	0,21		0,21		0,21		0,21		0,21		0,21	

Note: Values are given at the *** 1%. ** 5% and *10% significance level, respectively.

Table 3. Additive and multiplicative weighted, pooled OLS estimations with cluster robust standard errors of the effects of human capital on plant performance in combination with different forms of variety of knowledge in multi-plant firms in KIBS between 2000 and 2010 in Sweden.

	Model 1C		Model 1D		Model 2C		Model 2D		Model 3C		Model 3D	
Productivity (log)	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
HumCap (t-1)	.329***	.081	.579*	.318	.351***	.078	.270**	.110	.341***	.083	.444***	.099
SIM (log +1)(t-1)	-.185*	.105	-.353	.263								
REL(t-1)	.025	.039	.143*	.080								
UNREL(t-1)	-.134***	.034	-.082	.059								
*HumCap * SIM*			.162	.396								
*HumCap * REL*			-.262*	.151								
*HumCap * UNREL*			-.122	.109								
IND_SIM(log +1)(t-1)					-.052	.082	-.328**	.139				
IND_REL(t-1)					.139	.104	.083	.186				
IND_UNREL(t-1)					.021	.043	.048	.045				
*HumCap * IND_SIM*							.609***	.208				
*HumCap * IND_REL*							.119	.332				
*HumCap * IND_UNREL*							-.058	.052				
EDU_SIM (log +1)(t-1)									-.447	.541	-1.644***	.587
EDU_REL(t-1)									.090	.082	.239*	.137
EDU_UNREL(t-1)									-.079**	.036	-.036	.057
*HumCap * EDU_SIM*											1.635**	.721
*HumCap * EDU_REL*											-.322*	.185
*HumCap * EDU_UNREL*											-.109	.103
Worker_Age	.015***	.004	.0154***	.004	.017***	.005	.017***	.005	.015***	.004	.015***	.004
Plant_growth	-.001	.002	-.001	.002	-.001	.002	-.000	.002	-.000	.002	-.000	.002
Specialization	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000	.000
Urbanization (ln)	-.224	.579	-.176	.579	-.284	.580	-.290	.579	-.296	.586	-.194	.610
Ind_Div (ln+1)(t-1)	.046	.211	.061	.215	-.077	.172	-.077	.171	-.059	.193	-.045	.192
Reg_Div	-.189	.187	-.194	.189	-.167	.174	-.169	.176	-.171	.181	-.177	.180
Year dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes		Yes		Yes	
Observations	3226		3226		3226		3226		3226		3226	
Plants	549		549		549		549		549		549	
R^2	0.25		0.26		0.25		0.25		0.25		0.25	

Note: Values are given at the *** 1%. ** 5% and *10% significance level, respectively.

Table 4. Additive and multiplicative weighted, pooled OLS estimations with cluster robust standard errors of the effects of variety of education on plant performance in combination with different forms of variety of knowledge experiences in single-plant firms in KIBS between 2000 and 2010 in Sweden.

	Model 4A		Model 4B		Model 5A		Model 5B	
Productivity (log)	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
SIM (log +1)(t-1)	-.094	.147	.062	.159	-.011	.151	-.584**	.240
REL(t-1)	.146***	.037	.090**	.046	.113***	.039	.118**	.053
UNREL(t-1)	-.060*	.034	-.002	.040	-.032	.035	-.083*	.045
IND_SIM(log +1)(t-1)	-.068	.067	.204*	.120				
IND_REL(t-1)	.198***	.059	.095	.090				
IND_UNREL(t-1)	-.040*	.021	.005	.025				
IND_SIM SIM*			-.693**	.288				
*IND_REL * REL*			.229*	.126				
*IND_UNREL * UNREL*			-.032***	.012				
EDU_SIM (log +1)(t-1)					-.991***	.334	-1.682***	.462
EDU_REL(t-1)					.059	.052	.067	.074
EDU_UNREL(t-1)					-.088**	.041	-.101	.062
*EDU_SIM * SIM*							1.560***	.529
*EDU_REL * REL*							-.032	.053
EDU_UNREL UNREL*							.011	.021
Worker_Age	.012***	.003	.012***	.003	.011***	.003	.010***	.003
Plant_growth	-.004***	.001	-.004***	.001	-.004***	.001	-.004***	.001
Specialization	.000	.000	.000	.000	.000	.000	.000	.000
Urbanization (ln)	-.002	.421	-.064	.421	-.002	.420	-.003	.418
Ind_Div (ln+1)(t-1)	.648*	.384	.620	.379	.652*	.386	.665*	.384
Reg_Div	-.515**	.233	-.507**	.231	-.518**	.234	-.529**	.234
Year dummies	Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes	
Observations	5517		5517		5517		5517	
Plants	1187		1187		1187		1187	
R^2	0.19		0.19		0.19		0.19	

Note: Values are given at the *** 1%. ** 5% and *10% significance level, respectively.

Table 5. Additive and multiplicative weighted, pooled OLS estimations with cluster robust standard errors of the effects of variety of education on plant performance in combination with different forms of variety of knowledge experiences in multi-plant firms in KIBS between 2000 and 2010 in Sweden.

	Model 4C		Model 4D		Model 5C		Model 5D	
Productivity (log)	Coef.	SE	Coef.	SE	Coef.	SE	Coef.	SE
SIM (log +1)(t-1)	-.188*	.103	-.324**	.129	-.180*	.109	-.688**	.298
REL(t-1)	-.012	.039	.042	.052	-.017	.035	-.061	.083
UNREL(t-1)	-.180***	.039	-.204***	.062	-.159***	.040	-.219***	.058
IND_SIM(log +1)(t-1)	-.086	.085	-.323*	.172				
IND_REL(t-1)	.224**	.111	.375**	.191				
IND_UNREL(t-1)	.049	.045	.031	.049				
IND_SIM SIM*			.556*	.313				
*IND_REL * REL*			-.254	.177				
*IND_UNREL * UNREL*			.014	.021				
EDU_SIM (log +1)(t-1)					-.745	.635	-1.758**	.713
EDU_REL(t-1)					.062	.081	.022	.119
EDU_UNREL(t-1)					-.044	.044	-.073	.062
*EDU_SIM * SIM*							1.843**	.927
*EDU_REL * REL*							.040	.070
EDU_UNREL UNREL*							.028	.025
Worker_Age	.016***	.005	.017***	.005	.012***	.004	.012***	.004
Plant_growth	-.001	.002	-.001	.002	-.001	.002	-.001	.002
Specialization	.000	.000	.000	.000	.000	.000	.000	.000
Urbanization (ln)	-.175	.563	-.107	.547	-.192	.576	-.181	.576
Ind_Div (ln+1)(t-1)	.053	.181	.077	.187	.101	.207	.071	.205
Reg_Div	-.194	.176	-.191	.174	-.207	.186	-.202	.186
Year dummies	Yes		Yes		Yes		Yes	
Industry dummies	Yes		Yes		Yes		Yes	
Region dummies	Yes		Yes		Yes		Yes	
Observations	3226		3226		3226		3226	
Plants	549		549		549		549	
R^2	0.25		0.25		0.24		0.24	

Note: Values are given at the *** 1%. ** 5% and *10% significance level, respectively.

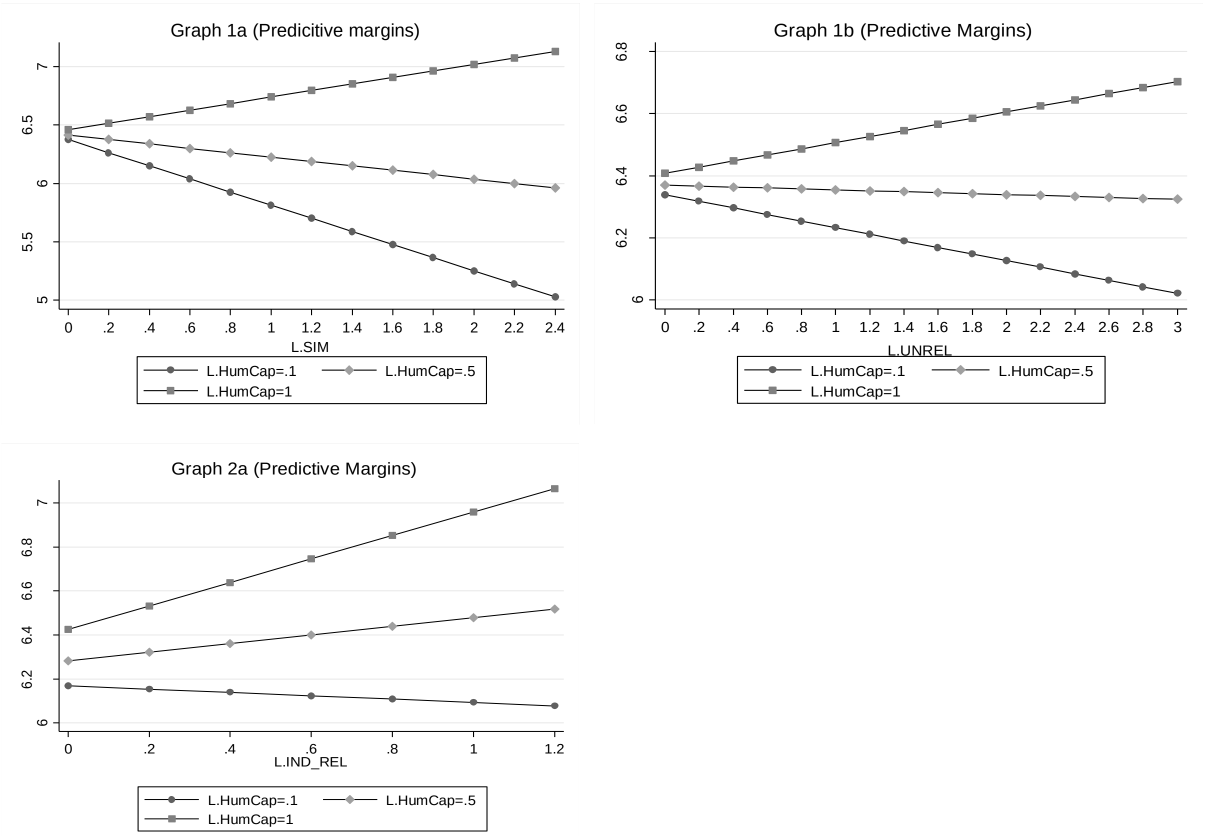

Figure 1. The effects of knowledge – and experience variety on plant performance at low, average and high levels of human capital ratios in single-plant firms. Graphs for significant interaction terms are shown.

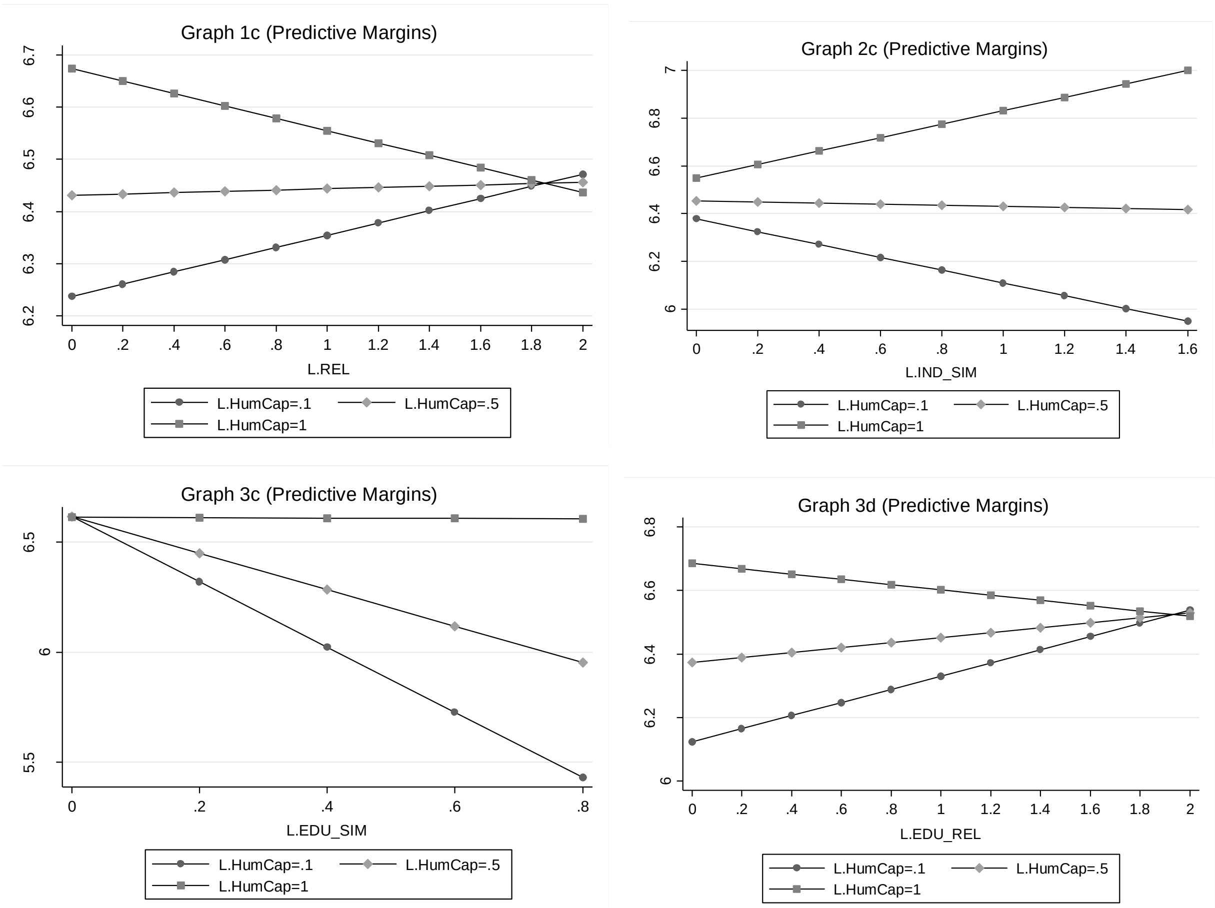

Figure 2. The effects of knowledge – and experience variety on plant performance at low, average and high levels of human capital ratios in multi-plant firms. Graphs for significant interaction terms are shown.

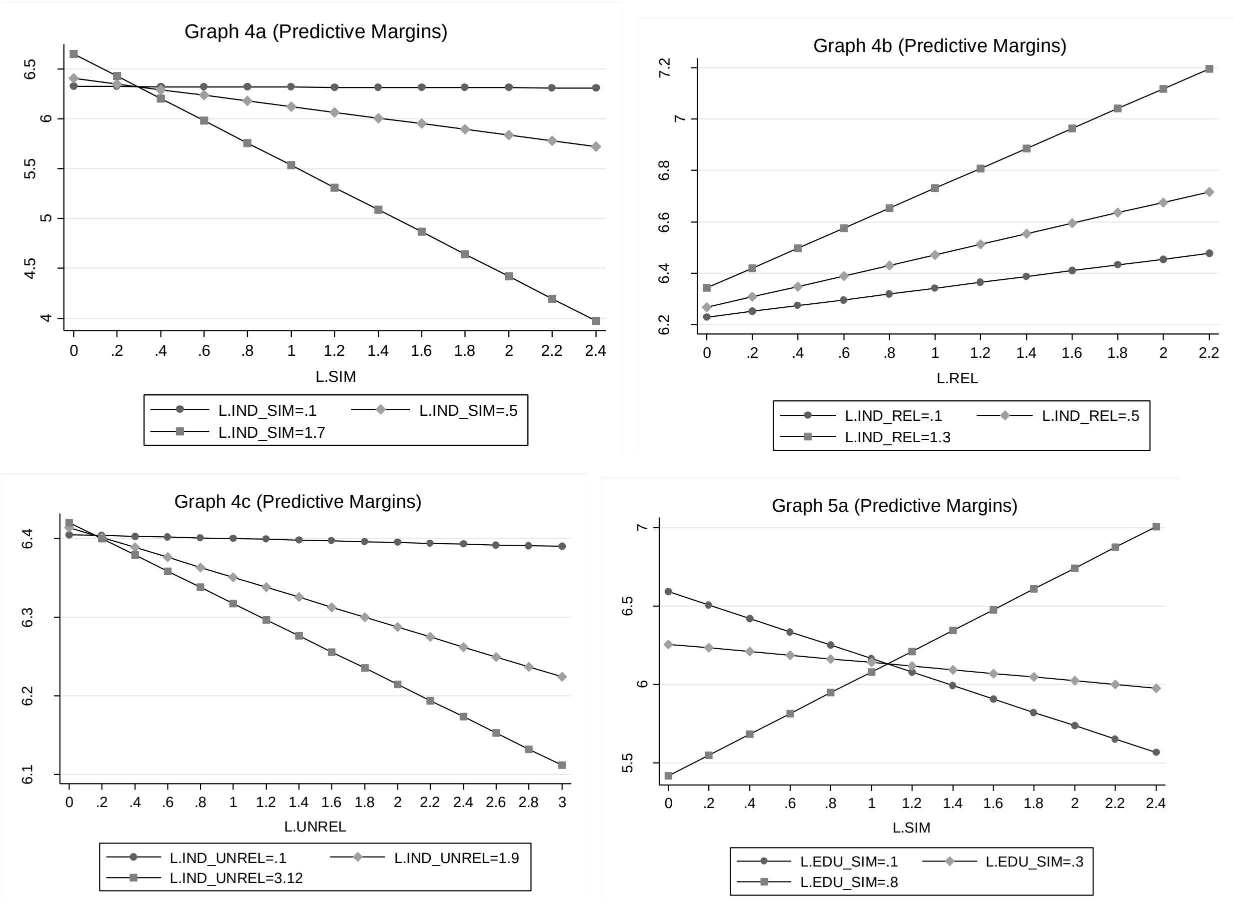

Figure 3. The effects of in-house knowledge variety on plant performance at low, average and high levels of similar knowledge exposure and unrelated industry experience, respectively, in single-plant firms. Graphs for significant interaction terms are shown.

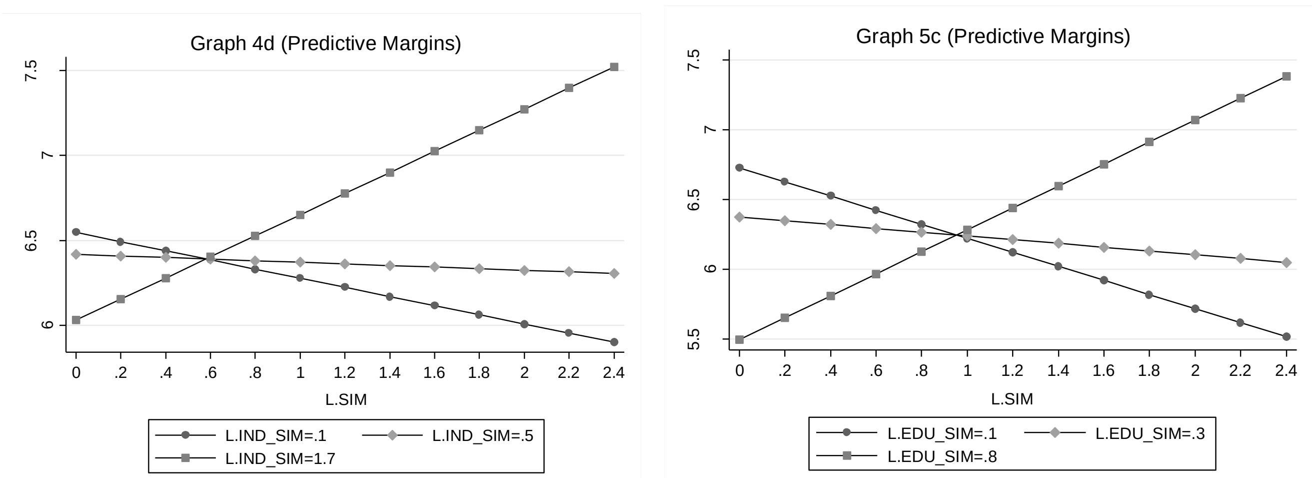

Figure 4. The effects of in-house knowledge variety on plant performance at low, average and high levels of similar knowledge exposure and unrelated industry experience, respectively, in multi-plant firms. Graphs for significant interaction terms are shown.