Comparing the impact of inter and intra-regional labour mobility on problem-solving in a Chinese Science Park

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ABSTRACT

Labour mobility of skilled employees is argued to have a positive impact on clusters, yet few studies have investigated how and whether this may be influenced by diverse geographic patterns of mobility. Through a study of R&D employees working in ICT firms in the Beijing Zhongguancun Science Park, we argue that regional institutions and the tacit routines of local firms are central in the development of labour skills. Regression analysis shows that while mobility enhances problem-solving capabilities, employees changing jobs singularly within the cluster will outperform those who come from outside. This emphasizes the importance of regional effects of mobility.

Key words: Labour Mobility, Knowledge Work, Clusters, China

INTRODUCTION

Labour mobility of high-skilled employees is argued to be an effective mechanism by which organizations can improve their access to human capital through "embodied" knowledge flows (ZIMMERMANN, 1995; CRESCENZI *et al*., 2007) and tap into valuable networks (MALMBERG and POWER 2005; CASPER and MURRAY 2005). There is similar enthusiasm for the notion that mobility can help organizations to generate flexible competencies (SCARBROUGH, 1999) and that it underpins network R&D structures (ARTHUR and ROUSSEAU, 1996; SAXENIAN, 1996).

Although such enthusiastic views of high turnover rates have been critiqued in some research by McCann and Simonen, (2005) in terms of congestion effects, RAATIKAINEN (2003) and LEININGER (2004) in China because they lead to the need to concede high salary rises and RAMIREZ (2007) because they weaken incentives for long-term investment in employee firm-specific skills, the main concern in this paper is to flag up the fact that studies examining the relationship between labour mobility and knowledge transfer, but whose epistemology and/or methodology is "a-spatial" i.e. do not take into account of where individual's careers are formed, overlook a key component of how knowledge and skills are developed and transferred. As BRESNAHAN *et al*., (2001), GERTLER (2003) and IAMMARINO and McCANN (2006) have argued, the development of both individual and organizational competencies tends to be "spatially sticky" and locally embedded. In the context of large clusters and high-technology agglomerations, there is therefore often a spatial dimension associated to the evolution of problem-solving abilities, and skills tend to co-evolve and "match" firm competencies in a region through a joint-learning dynamic. This argument suggests that recruiting employees that are locally mobile (intra-regional mobility) could have a significantly different impact than if that recruitment is drawn from those with a geographically dispersed career history (inter-regional mobility). This may be the case even after controlling for formal differences in human capital and networking capability between employees from within and outside of the region.

Relying primarily on insights from evolutionary economic geography that emphasizes firm-specific routines and institutional geography that stresses the importance of locations for agglomerations, the paper examines the implication that differences in geographical patterns of mobility may have on learning within the firm. We propose that, in the context of high-technology clusters, while mobile employees are more likely to successfully engage in developing new solutions and procedures in innovation projects compared with their less mobile counterparts, local mobility will enhance this problem-solving capability. The paper goes on to explore some of the mechanisms by which these effects arise by comparing different forms of recruitment and insertion in networks between R&D workers with different geographical patterns of mobility.

These questions are examined empirically through an analysis of a unique survey of 381 R&D managers and employees working in 71 Chinese ICT companies in the Beijing Zhongguacun science park, China's largest high-technology science park. A particular advantage of this survey is that it allows us to compare inter and intra-regional patterns of mobility, as well as other related issues such as recruitment practices and networks. The question this paper raises is moreover particularly relevant for Chinese science parks that, as the Chinese economy has boomed, have experienced dramatic increases in mobility rates, raising important policy and practitioner questions as to the benefits of mobility for high-technology firms.

MOBILITY AND AGGLOMERATION ECONOMIES

Discussions on the impact of labour mobility date back at least to ARROW's (1962) article on the public good aspect of knowledge, where it is argued that labour mobility makes it impossible to appropriate information. In this view, mobility is considered an important mechanism for knowledge spillovers as high-skilled employees move between jobs or form their own spin-off companies (ARTHUR and ROUSSEAU, 1996; POWELL and GRODAL, 1997; HAKANSON, 2005; ZUCKER *et al*., 1995; AGRAWAL *et al.,* 2006). High mobility is also associated with helping to overcome problems of unemployment (OECD, 2001) and increasing efficiency of job search (MOEN, 2005) thereby improving the efficiency of labour markets. Thus, with some exceptions, most of the empirical evidence suggests that companies benefit by being located in regions that have higher levels of labour mobility and, although there is some debate concerning the different mechanisms by which this impact occurs, this has repeatedly been used to support policies aimed at lifting the barriers that hinder the movement of workers between companies.

However, the importance of local mobility has been highlighted as a key feature of knowledge flows amongst the high-skilled (BRESCHI and LISSONI, 2009). Therefore, geographical differences in patterns of mobility, and in particular local versus inter-regional mobility is an important part of the debate on knowledge transfer, for where individuals develop their skills is likely to impact the performance of R&D managers and workers. This is a key issue for the study of the relationship between work and learning at the firm, in part because some existing mainstream economic models that overly rely on human capital explanations to argue that mobility makes labour markets more efficient, such as for example LEWIS and YAO (2006), will fail to account for why, even after controlling for human capital, problem-solving capabilities of individuals with different geographical patterns of mobility and career structures may continue exist. Thus, the impact of human skills in a firm or a region will depend not solely on the quality or quantity of human capital, but on a range of factors including the ability to match supply of skills with demand and how companies use existing skills and training (RODRIGUEZ-POSE and VILALTA-BUFI, 2005). The next section discusses two perspectives from the economic geography literature that specifically take into account uneven spatial patterns of economic activity and thus may provide more plausible explanations for the “local” effect of labour mobility.

EVOLUTIONARY PERSPECTIVE

The first of these comes from an emerging evolutionary economic geography perspective that has adapted concepts from evolutionary economics to help understand regional dynamics. Evolutionary economics explains knowledge generation and innovation at the level of the firm through the development of firm-specific routines that are characterized by informal norms, rules and habits that become important intangible assets for organizations. These are largely tacit in nature and hence generate untraded interdependencies (NELSON and WINTER, 1982; DOSI *et al.*, 1988). Routines therefore are the essential organizational context that influences how employee skills are effectively applied.

Evolutionary economic geography also focuses on routines but examines their distribution across geographical spaces. Although no a-priori assumptions are made regarding the existence of spatial agglomerations, local routines may emerge as a result of spin-offs from a parent firm or local labour mobility, which more than likely may involve local path dependencies as firms and employees stay in the region (BOSCHMA and FRENKEN, 2009). Thus, routines can extend from the organization and affect the location as firms and employees interact within the region.

From this perspective, the significance of labour mobility lies firstly in terms of encouraging knowledge diffusion. Mobility can thus be considered a vehicle for the extension of local routines within a cluster. Hence, while much knowledge is seen as embodied in organizational routines and therefore hard to exchange, tacit knowledge spillovers through individuals can occur more easily when actors are geographically proximate (BRESCHI and LISSONI, 2003). A number of studies of successful regions and labour mobility suggest this is the case. Case studies by SAXENIAN (1996) and BEST (2001) of Silicon Valley and Route 128 respectively emphasize that intra-regional labour mobility has been a key factor facilitating firm-level flexibility, rapid learning and specialization. Similarly, the importance of "localness" of certain practices is underpinned by physical proximity for the transfer of tacit knowledge (ALMEIDA and KOGUT, 1999; COOPER, 2001; POWER and LUNDMARK, 2004), which can be facilitated by mobility within regions. It has also been argued that because many firms emerge from spin-offs or will be related in different ways to similar occupational groups and supply-chains, local workers will tend to understand better the local market and establish a good skills-match, hence, there will be specific advantages to firms from recruiting within the region (FESER, 2002).

PATTON and KENNEY (2005) make a similar valid point that successful clusters are characterised not just by the existence of leading firms, but by a network of firms that facilitate entrepreneurs to create new firms, particularly spin-offs. Thus the movement of engineers and scientists between large firms, start-ups and service organizations create local traded and untraded interdependencies that help create dynamism in the local system.

Underlying the notions of the above authors therefore is the assumption that greater local labour mobility will provide not only access to human capital, but also tacit knowledge that emerges through the development of local industries and in some cases, from similar occupational groups. This may therefore facilitate integration of local employees. On this basis, we might predict that intra-firm mobility would help firstly to diffuse routines from for example a dominant regional firm, if this indeed exists. Perhaps more significantly, it may also help to consolidate common regional habits and practices. Through local recruitment, firms are able to learn from the good and bad practices of neighbouring firms. This is certainly liable to occur if they are in the same supply chain, but even in cases where there aren't direct business type links, firms might imitate other firm routines in areas such as for example adoption of human resource practices, to attract high-skilled labour in the region. We would therefore expect locally recruited R&D employees to be more easily integrated into existing firms and have a more positive impact in problem-solving routines than R&D employees recruited from outside the region.

A similar proposition can be made if we look at the concept of path dependence, another feature of the evolutionary economics approach. This is where organizational routines within economic sectors build up over time and initiate certain trajectories of technologies with long-term adoption (DAVID, 2001). Thus, at the level of the region, the complex interweaving of organizational competencies, supply chains and informal networks establishes distinguishing regional heuristics. The concept of path dependence is highly relevant for policy makers for there is a balance between generating benefits from a relatively coherent system with stable structures and achieving a degree of openness to new ideas. Regional failure may therefore be interpreted as a reflection of when economic actors become locked-in to established ways of doing things (GRABHER, 1993; HASSINK, 2005).

As discussed earlier, intra-regional labour mobility can be an important vehicle in establishing regional path-dependency through the diffusion of routines. By the same token, precisely because it is not specific to the local industry, inter-regional labour mobility can be a vehicle that not only increases the density of the local skills pool, but also changes its quality in terms of variety and cultures it may contain (DE BLASIO, 2006; OTTAVIANO and PERI, 2006). The work by ESSLETZBICHLER and RIGBY (2005) and RIGBY and ESSLETZBICHLER (2006) in the US machine tool industry also indirectly backed this idea. They found that intra-regional variety of plants (in terms of production techniques) was persistently lower than inter-regional variety of plants. Consequently, when firms recruit new workers from other firms in their own region, these are less likely to bring new knowledge into the company, because local firms in the same sector tend to look more alike.

However, despite its potential significance, research specifically examining the impact of inter-regional labour mobility either in terms of firm level learning or on employee skills is more sparse and patchy. The limited evidence that is available would seem to suggest that inter-regional mobility brings greater diversity, but that its impact in firms depends on the absorptive capability of organizations. This argument has been used to explain why US firms appear to have benefited more than EU firms from migration (CRESCENZI *et al.,* 2007). The strength of its research universities, the innovation regulatory framework, the more numerous start-up firms and the higher degree of specialized R&D are all argued to have contributed to making US firms more open to technological shifts and radical innovation and so able to integrate diverse skills more easily. By contrast, the weaker entrepreneurial culture, resistance to organizational change and obstacles to recombining staff in response to technology and market shifts has made EU firms less able to integrate diverse skills (Ibid.). Hence, diverse territorial dynamics have played an important role in the integration of skills.

The work on "related and unrelated variety" by BOSCHMA *et al.,* (2009) and ERIKSSON (2010) is particularly relevant here. BOSCHMA *et al.'*s study (2009) of productivity of Swedish plants finds labour recruited from outside the region only has a positive effect when employees have "related" (i.e. not identical but not unrelated) skills. Thus skills from outside the region are only likely to be absorbed and utilized when there is a cognitive or sectoral similarity. ERIKSSON (2010) similarly finds that "neither too little nor too much" geographical and cognitive proximity of labour mobility has a positive effect on labour productivity.

INSTITUTIONAL PERSPECTIVE

An alternative but complementary explanation for why different spatial patterns of mobility may be associated with diverse patterns of learning is provided by institutional explanations that have an established tradition in economic geography (MACKINNON *et al.,* 2009). In this view, institutions are embedded in geographically localized practices, which imply that localities are a relevant unit of analysis that simultaneously constrain, mould and enable individual habits, preferences, values, and actions (Ibid.). Institutional explanations are relevant for individual learning although they rely less on cognitive explanations than on the establishment of common rules, signposts and incentives. Thus, while cognitive arguments will provide one set of explanations for how learning will take place within and across regions, this process can be strongly mediated, reinforced and shaped by institutional factors. For example, an important part of mobility is associated not just with formal knowledge transfer, but establishing informal institutions such as trust, screening and socializing (RODRIGUEZ-POSE and CRESCENZI, 2008). Formal institutions that coordinate regional patterns of industrial relations and wage setting can also create expectations and behaviours that may cause mismatches with employers in other regions. Thus, as CAMAGNI (1995) underlined, routines do not diffuse in the air. It is for example significant in BOSCHMA *et al.*, (2009) that inflows of "unrelated" skills to firms actually contributed positively to plant performance, but only when these were recruited in the same region. This suggests that institutional factors associated to the local context, other than formal cognitive aspects of skills, may be playing a role facilitating an impact on firm performance.

Evolutionary and institutional approaches in geography reinforce the argument that local mobility may provoke a different learning dynamic in firms than if the mobility is geographically dispersed. Knowledge workers moving jobs predominantly within a local area can be expected to be influenced by and also help reinforce local routines that will facilitate the integration of local skills with firm capabilities. Furthermore, the existence of institutions, particularly in those areas that influence form of recruitment, training and other areas of employment in high technology areas may also reinforce a better match between local recruits and firms. This was found by BRESCHI and LISSONI (2003) when looking at Italian inventors (patent applicants), where local mobility reduced search costs and by SONG *et al.*, (2003) who emphasized that local mobility will be better at matching skills by establishing a type of "learning-by-hiring".

The discussion leads us to suggest that mobility is likely to have a positive learning dynamic in organizations. It also suggests that the impact of managers and high skilled employees that have predominantly moved jobs within a local area may be different from those whose career history has involved movement outside the regions. This is because agglomerations of firms and local institutions may combine to create unique and difficult to replicate conditions that facilitates the integration of workers moving into new jobs. Inter-regional mobility on the other hand may bring new skills and greater diversity to firms, although as discussed, the impact may depend on the absorptive capability of organizations and the degree of relatedness of these skills.

LABOUR MOBILITY IN CHINA AND GUANXI LINKS

A cursory review of China's emerging market economy suggests that mobility of high-skilled labour is an important feature of its science parks. Evidence from the business and professional press suggests that Chinese high-tech firms experienced double digit labour turnover and difficulty in retaining qualified staff, leading to the need to concede high salary rises (RAATIKAINEN, 2003; LEININGER, 2004). Important changes in the structure of labour markets occurred as part of an attempt to liberalise direct state control of firms in the economy. Thus, labour market reform evolved very quickly from state control in the assignment of labour between 1956 and 1979, where no real labour market existed and jobs were allocated administratively and usually for life, to mandatory labour contracts in all organizations (SUTTMEIER 1997). This opened the door to greater inter-firm mobility. Indeed, in the decade of the 1990s, the combination of rapid growth of China's high-technology sector, the large numbers of lay-offs from state sector firms (HUANG 2008) and the high concentration of employment growth in government sponsored science parks created a highly dynamic labour market in terms of voluntary and non-voluntary mobility.

Although few English language studies have directly analyzed the impact that these high levels of mobility experienced in the Chinese industrial and science parks have had on productivity, innovation performance or cross-organizational knowledge spillovers, those that have addressed this issue have noted some concerns. For example, SAXENIAN (2003) has suggested that 20%-30% annual turnover creates problems for retention of knowledge especially for small firms, particularly if there are no sanctions to employees leaving half-completed projects or if character references and work portfolios are not used as a means of assessing past performance.

Interest has particularly focused on the influence of *guanxi* relationships, which loosely translates as "connection" or "relationship" and the impact it may have on so-called "learning-by-hiring" (SONG *et al.*, 2003). According to SAXENIAN (2003), *guanxi* have historically served as an important organizing principle for Chinese economic and political life and investing time in establishing relationships with officials, important managers in companies and others in key positions is necessary to achieve most goals, including accessing jobs. Moreover, *guanxi* typically involves reciprocal obligations and indebtedness as favours have to be returned (GOLD, 2002), hence they usually are associated with some sort of transaction cost.

Guanxi thus poses a challenge for many Western scholars, who assume that recruitment and job search rely on principles of meritocracy. For example, GRANOVETTER's (1973) celebrated contribution suggested that the use of personal contacts for finding a job was likely to mean better information for the employees and employers. This assumed the mobilization of professional networks to provide a good match for jobs and avoid redundant information about job openings. Based on studies in the U.S., he also argued that the most effective job movements are those where information was provided through occupational ties and where ties are "weak", in other words, where workers are not tied and indebted by intense relationships to define their choice of jobs[1]. However, empirical research by HUANG (2008) and BIAN (1997) found that strong ties play a more important role in accessing desirable jobs in China and East Asia generally than in the West. Thus, the significance of *guanxi* ties for accessing jobs is that it may weaken the assumed positive relationship between labour mobility and improved performance for the individual and the organization for which he/she works for and may also have a significant impact on the geographical spread of labour mobility and confound the differential impact of local vs. inter-regional mobility. It is therefore an important factor to take into account if we want to disentangle the distinct moderating role of location.

Case study evidence by HUANG (2008) and BIAN (1997) also found that *guanxi* ties is used extensively for recruitment in publicly-owned organizations. Moreover, those recruited through these networks underwent little or no appraisal of productivity potential before appointment. By contrast, *guanxi* was much less relied upon to get jobs in private sector firms.

The above discussion highlights the double-sided view of labour mobility, where institutions, including those influencing how individuals are recruited and trained can strongly influence its impact in the region and the firm. The following section presents the methodology used to compare spatial patterns of mobility.

RESEARCH QUESTIONS

The discussion has emphasized that the region represents an important arena within which skills are formed and applied within the context of work and employment in firms. It suggests that recruitment of locally mobile employees into R&D departments in a science cluster may be more beneficial compared to individuals who have a more geographically dispersed career history, primarily because the local nature of learning will facilitate integration of skills in firms. This is likely to be particularly the case where clusters differ a great deal in their ability to create knowledge, leading to a degree of asymmetric knowledge and capabilities between regions. It is therefore hypothesised that the impact of mobility of R&D employees on their problem-solving ability in the workplace will differ significantly according to whether they have developed careers and moved jobs in or outside of the cluster. The proposition is also made that the impact of mobility may be influenced by the manner in which individuals access new jobs. Closed systems of recruitment enlightened more by *Guanxi*-type customs than meritocratic principles may be relevant in the Chinese context and negatively influence the impact of labour mobility on the performance of individuals in firms. The literature review suggested that this pattern may be more pronounced in wholly state-owned firms than privately owned and managed firms.

DATA COLLECTION

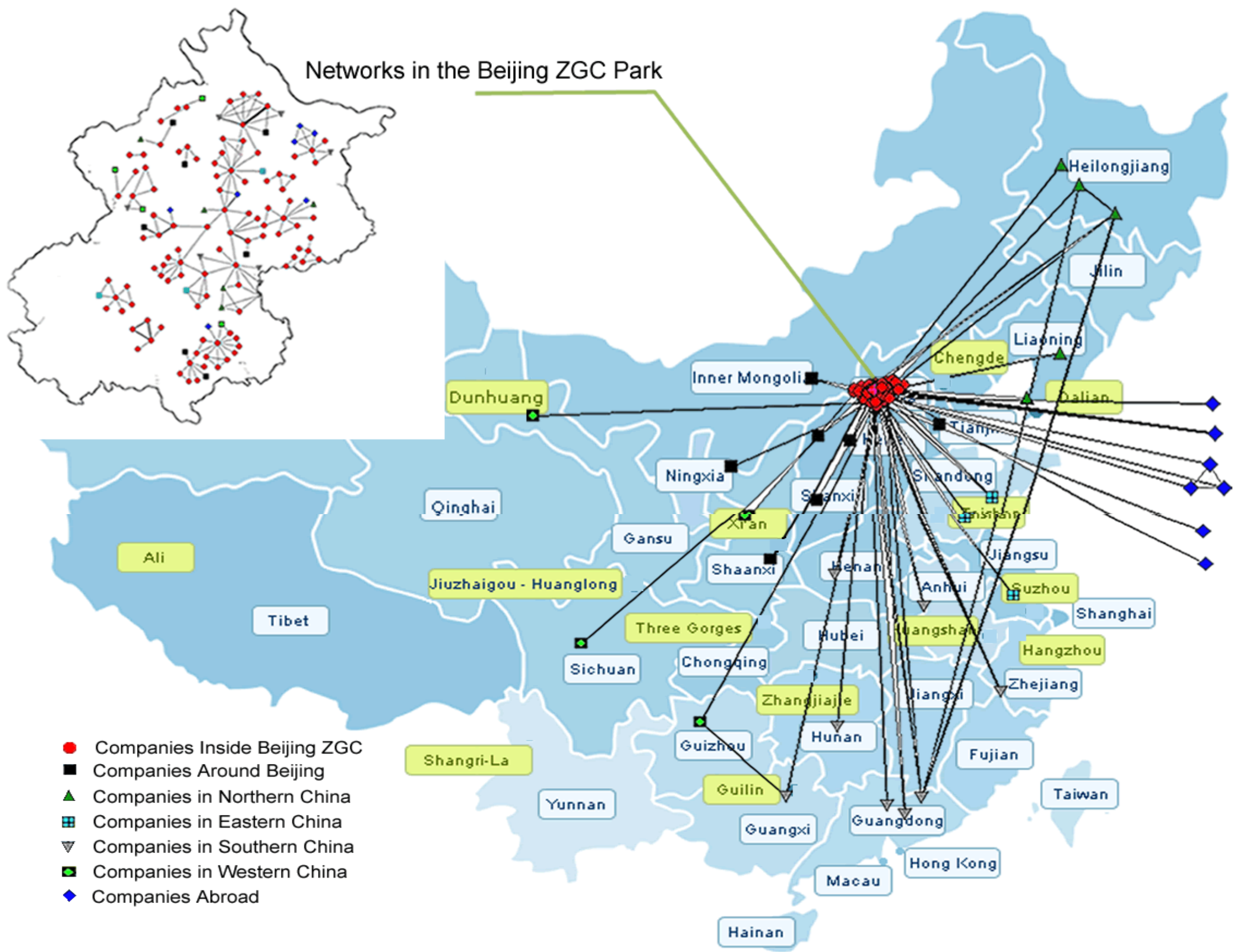
The empirical investigation is based on a study of R&D employees working on innovation projects in Chinese ICT firms located within the Beijing Zhongguancun (ZGC) high technology park. Covering the northwest of Beijing, ZGC is China's first and largest high technology science park. Since its inception, spin-off companies from the large number of universities located in ZGC have become some of the best known in China, such as the Founder Group of Beijing University; the Tongfang group of Tsinghua University; and Lenovo (formerly Legend). Within the ZGC Park there are 68 universities and 213 scientific research institutes, including the Chinese Academy of Sciences (academics of the Chinese Academy of Sciences and Chinese Academy of Engineering comprise 36 per cent of all academics in China) (WANG *et al.*, 2000).

It was decided to use the opportunity of a congress of ICT firms located in the ZGC Park in Beijing to invite attending R&D managers to participate in a survey. Aside from facilitating access to firms, this non-probability method of identifying firms introduces some randomness into the sample, although some bias is possible, since those firms attending the congress may have been part of a particular network of organizations. A quota system was used, whereby a target of firms fulfilling certain criteria was established and collection of data stopped once that target was reached. This method typically involves interviewing or asking certain *types* of respondents to answer questions on the survey. This method proved more straightforward than other forms of stratified sampling because the type of firms to be included was decided beforehand.

Given the emphasis on studying the career and other labour market activities of Chinese R&D employees, the target organizations approached consisted of indigenous Chinese ICT companies located in the ZGC Park with an R&D department. The relative lack of knowledge of the practices of Chinese-owned vis-a vis multinationals firms in this area suggested to us that a study of Chinese firms would be more revealing. The protocol used to undertake the survey consisted of approaching a senior R&D manager at the congress (or if he/she was not available, a senior person in R&D) to participate in the research. If the answer was affirmative, the senior R&D managers were contacted at a later date and asked to choose a major innovation project in the company over the past three years and to nominate up to 10 R&D employees that worked in the above project, who in turn were asked to answer questions in a survey and to submit these on-line. This method of choosing R&D employees is more likely to suffer from bias, since it is based on the recommendations of the R&D manager[2]. Some care therefore needs to be taken when generalizing these results to a wider population of ICT firms undertaking innovation in the ZGC Park. The target was set at 400 R&D workers, in part due to pragmatic reasons associated with the time it would take to gather the data and resources available, although this number was felt to be sufficient to undertake planned statistical analysis.

The final data collection was based on a survey of 381 R&D employees working on innovation projects in 71Chinese high-technology firms located in the ZGC Park, though missing items meant our empirical analysis was based on 314 responses. Of these, 122 workers provided detailed information on career histories. Figure 1 below illustrates the spatial range of previous affiliations of R&D employees. As would be expected, the vast majority of previous affiliations are concentrated in the Beijing region. Outside Beijing, the geographical range of previous affiliations is broad rather than concentrated, including some employees that have worked overseas

Figure 1
Regional pattern of mobility of R&D employees



VARIABLE CONTRUCTION

The first question that is investigated is whether inter and intra-regional geographical mobility will impact the problem-solving capability of R&D employees working in firms in the ZGC Park in diverse ways. We derive the dependent variable from the question "do you regularly develop new solutions and procedures" on the innovation project on a 4-point Likert scale. It was constructed on the basis of the respondent's description of his/her work in the innovation project. This measure parallels a number of studies that use indicators of work organization and individual problem-solving to evaluate innovative efforts in firms including MENDELSON and PILLAI (1999), MICHIE and SHEEHAN (1999) and RAMIREZ and LI's (2009) work on China. More specifically, SCOTT and BRUCE (1994) suggested a relationship between innovation and problem-solving style of individuals and, drawing on PAYNE *et al.*, (1990), argued that the fit between problem-solving and work environment helps to determine performance in R&D on the job. ARUNDEL *et al.*, (2007), through a broader study linking data on working conditions in Europe and innovation mode indicators for the CIS survey, also found that in countries where learning and problem-solving on the job are higher, innovations are developed to a greater extent through the firm's in-house creative efforts. Following this tradition of research, the dependent variable in the paper therefore reflects the degree to which individuals successfully engage in process and procedural innovations in R&D projects in firms[3].

Table 1 Definitions of the explanatory variables

Variables	Definition
Log(Tenure)	Logged number of years the respondent has worked for the current employer
Log (Experience)	Logged number of years since respondents finished their education minus their years in current employment.
Education	A dummy variable. If the respondents had a Master degree or higher level of education, Education = 1, and 0 otherwise.
Seniority	A dummy assessing the individual's position of responsibility within the organization. If the respondent held a managerial position or she/he isa senior scientist/engineer, Seniority =1, and 0 otherwise.
Mobility	The number of jobs that the respondent held in the last 5 years, not including the current job.
Internal - Learning	Standardized score based on the respondent's assessment of importance of formal internal training as a learning source on a 4-point Likert scale.
External - Learning	Standardized sum score based on the respondent's assessment of importance of the following learning sources: (1) attending conferences; (2) overseas visits; (3) training outside of company but inside the ZGC park; (4) communications with people outside the company (e.g. through group email, message board or chat room); and (5) informal communication with acquaintances outside the company dealing with similar problems.
Location	A dummy measuring whether workers that had moved jobs outside ZGC park. If she/he has moved outside ZGC, Location = 1, and 0 otherwise.
Open - Market	A dummy reflecting relatively open methods of recruitment in the current job. If the respondent obtained her/his current job through open-market methods, Open-Market = 1 , and 0 otherwise. This variables groups together R&D worker responses in the survey that reflect relatively meritocratic and open forms of recruitment. These include recruitment "by means of an employment agency", "Job Fair at a university" and "responded to advert in press or the Internet". Other answers, including "recruitment by an informal peer network" were taken as reliant on *Guanxi* type relations.
Selection	A dummy measuring whether a knowledge worker has reported a previous affiliation. Selection = 1 when the respondent had a previous employment, and 0 otherwise.

The independent variables combine human capital variables likely to influence individual skill levels and action-oriented learning activities likely to influence performance. The human capital variables follow BECKER's (1962) well-known contribution,that originally used different measures of skills to explain variations in earnings. These measure the level of skills and experience gained inside and outside the organization. In tables 1 and 2, *Log(tenure)* represents the logged number of years the respondent has worked for the current employer. *Log(Experience)* is the logged number of years since respondents finished their education minus their years in current employment. This variable indicates broader knowledge of the labour market. Educational background was controlled by the variable *Education*. It takes a value of 1 when the respondent has a Master degree or higher level of education, and 0 otherwise. *Seniority* is a dummy assessing the individual's position of responsibility within the organization. It takes a value of 1 if the respondent is a senior scientist/engineer or holds a managerial position and 0 if she or he is a non-management technical employee within R&D department. Both *Log(Tenure)* and *Seniority* reflect the R&D employee's firm specific knowledge. In terms of action-oriented learning activities, our main variable of interest, *Mobility,* is measured as the number of jobs held in the last 5 years, not including the current job.

Given our focus on measuring problem-solving on innovation projects rather than productivity, two variables were used to measure the degree to which R&D employees with a history of mobility are engaged in learning inside or outside the organization. The first variable, termed as *Internal-Learning*, is drawn from the respondent's assessment of the importance of internal training as a source of learning about new technologies or managerial methods. The second variable that we shall call *External-Learning* emerged from an exploratory factor analysis of responses to whether five external sources of learning contributed to individual problem-solving. It is the sum of the following five variables: attending conferences; overseas visits; training outside of company but inside the ZGC Park; communications with people outside the company (e.g. through group email, message board or chat room); and informal communication with acquaintances outside the company dealing with similar problems. Reliability analysis for the smaller sample of 122 observations gave a Cronbach's alpha value of 0.5910 which was considered marginally acceptable. This variable is a particularly important measure since it emphasizes inter-firm knowledge transfer. In our estimation, both internal and external learning variables were standardized and both were measured using on a four-point Likert scale.

Next, a variable called *Location* was created to distinguish R&D employees that had moved jobs exclusively within the ZGC Park (*Location* =0), from those that have had some mobility outside (*Location* = 1). We examine if there exists any interaction effect between where R&D employees have moved jobs and the number of previous employments, by creating the variable *Location* $\times$ *Mobility*. Similarly, it can be investigated if there exists an interaction effect between moving jobs and the degree of external learning by creating the variable *Location* $\times$ *External-Learning*. A binary variable called *Selection* was created in the regression analysis to measure whether an R&D employee has reported a previous affiliation. Selection equals 1 when the respondent had a previous employment, and 0 otherwise. This variable is used to check if there is any significant difference in individual problem-solving ability between workers that did not move jobs in the past 5 years from those reporting movement of jobs between firms.

Table 2 compares the summary statistics between the sample of all 314 respondents and this subsample of 112 workers. The average levels of mobility of this sub-sample is higher, therefore as expected, workers in this subsample are more experienced and have a shorter period of tenure. For the subsample used in our estimation, the correlation matrix and summary statistics for explanatory variables are reported in Table 3. The possible effect of multicollinearity with Variance Inflation Factors (VIF) was examined and it was found that VIF coefficients for all variables is less than 2. According to BESLEY *et al.*, (1980) multicollinearity is therefore not considered a serious problem in our case.

Table 2 A comparison of summary statistics of whole sample of R&D employees and the subsample

	The 314 Respondents				The 122 respondents with detailed career			
Variable	Mean	Std.Dev.	Min.	Max.	Mean	Std.Dev.	Min.	Max.
Prolem solving ability	1.771	0.822	0	3	1.877	0.778	0	3
Log(Tenure)	0.494	0.905	-0.693	1.946	0.300	0.947	-0.693	1.946
Log(Experience)	-0.022	1.515	-2.303	3.157	0.643	1.467	-2.303	2.970
Education	0.258	0.438	0	1	0.254	0.437	0	1
Seniority	0.385	0.487	0	1	0.410	0.494	0	1
Mobility	0.605	0.951	0	4	1.557	0.919	0	4
Internal-Learning	-0.005	0.988	-2.435	1.115	-0.022	0.993	-2.566	1.174
External-Learning	-0.008	0.991	-2.805	2.406	-0.064	0.996	-2.567	2.433

Table 3 Correlation Matrix of Explanatory Variables

		Mean	Sd.Dev.	1	2	3	4	5	6	7	8
1	Log(Tenure)	0.300	0.947								
2	Log(Experience)	0.643	1.467	-0.438**							
3	Education	0.254	0.437	-0.002	0.149						
4	Seniority	0.410	0.494	0.252**	0.125	0.318**					
5	Mobility	1.557	0.919	-0.053	0.253**	0.035	0.239**				
6	Internal-Learning	-0.022	0.993	0.060	0.045	0.017	0.125	0.036			
7	External-Learning	-0.064	0.996	0.119	-0.210*	-0.027	-0.093	-0.089	0.323**		
8	Location	0.279	0.450	0.102	0.05	-0.027	0.188*	0.201*	0.083	-0.037	
9	Open-Market	0.738	0.442	-0.144	-0.108	-0.166	-0.071	0.017	0.031	0.118	-0.045

N= 122; ** $p < 0.01$, * $p < 0.05$.

ANALYSIS AND FINDINGS

Because the dependent variable "problem-solving ability" is measured in a four-point ordinal scale, the ordered logit regression technique is used in our estimation. In ordered logit models, an underlying score is specified as a linear function of the covariates and random errors. Outcome j is observed when the underlying score falls within the range of two cut-points κ_{j-1} and κ_j. In this study, given the dependent variable takes values from a 4-point Likert scale, the probability of a given observation taking the value of j (j= 1, 2, 3, and 4) is specified as:

$$\begin{aligned}\Pr(y_i = j) &= \Pr\left(\kappa_{j-1} < \mathrm{X}_i\beta + \mu_i \le \kappa_j\right) \\ &= \frac{1}{1+\exp(-\kappa_j + \mathrm{X}_i\beta)} - \frac{1}{1+\exp(-\kappa_{j-1} + \mathrm{X}_i\beta)}.\end{aligned} \quad (1)$$

Here, the random error μ_i is assumed to follow a logistical distribution. X_i is the covariate vector and β is the coefficient vector to be estimated. κ_j ($j = 1$, 2, 3 and 4) are the cut-points to be estimated along with the covariate coefficients β. By default, κ_0 is set as $-\infty$ and κ_4 is defined as $+\infty$. In our analysis, we need to estimate both the coefficient of covariates X_i and the three cut point, κ_1, κ_2 and κ_3. In ordered logit models, the actual values taken on by y_i are not important or irrelevant, as long as the rank order of the values remains the same. If we define the odds as $\Pr(X_i\beta + \mu_i > \kappa_j) / \Pr(X_i\beta + \mu_i \leq \kappa_j)$, then the coefficients of covariates can be interpreted as the logged odds ratio. In our context, a positive significant coefficient would mean that the larger the covariate is, the more likely reports a high score on the Likert scale (or more engaged in problem-solving). The larger the magnitude of the estimated coefficient, the greater the odds ratio.

It could be argued that R&D workers belonging to the same firm or working on the same project may demonstrate similar patterns due to unobserved fixed effects. Ideally, this could be controlled for by including a set of dummy variables capturing firm or project effects. In our cross-sectional dataset however, 122 R&D employees were working for 44 firms. If we employ this estimation strategy, we would have to incorporate too many dummies, which will inevitably bring in too much noise. As an alternative, we relax the usual requirement that the observations be independent and report a robust standard error allowing for intra-firm correlation. In other words, we assume that the observations are independent across firms but not necessarily within firms. In estimation with maximum likelihood technique, this treatment will affect the standard errors but not the estimated coefficients.

Insert Table 4 about here

RESULTS

Our main findings and estimation results are reported in Table 4. Column 1 of table 4 lists the result of the regression based on an estimation of all respondents when the variable *Selection* is incorporated. It is quite clear that the estimated coefficient of *Selection* is not statistically significant after human capital factors are controlled for, implying that there is no big difference in terms of individual-level innovativeness between workers who have reported previous affiliations and those who have not. Therefore we proceed to estimate the impact of mobility based on a subsample containing those workers who have previous job experience only.

Column 2 of table 4 gives the estimation when the variable *Location* is taken into consideration. Although both *Mobility* and *External-Learning* make a significant contribution to individual problem-solving, the estimated coefficient of *Location* is not significant, suggesting that the direct impact of *Location* is probably trivial. Nevertheless, when the interaction term *Location* × *Mobility* is incorporated in column 3, its estimated coefficient is found to be negative and significant. This indicates that *Location* has a negative moderating effect on the relationship between mobility and problem-solving ability. In other words, the positive impact of mobility is diminished for workers who have moved jobs outside Beijing. This finding lends support to our argument that at least part of the knowledge that can be effectively transferred by workers' mobility is sticky and locally embedded.

The moderating role of the geographical spread on the relationship between mobility and problem-solving capabilities may be undermined if mobility is strongly related to the extent to which knowledge works gain external knowledge. It could be argued that knowledge workers with a high-level mobility would have more access to external sources of knowledge, such as ex-colleagues, and thus attach a higher importance to external learning. If this is the case, the significant moderating role of *Location* on the impact of mobility may be capturing the impact of external-learning. We have two different ways to rule out this possibility. First, when we compared the importance of external learning between the two groups of workers with different Location values, we noticed no significant difference. This is confirmed in Table 3 by our observation that the correlation coefficient between the two variables mobility and external-learning is not significant, although positive.

As a further check it was also possible to investigate whether *Location* moderates the contribution of external learning on innovativeness. When the interaction terms in column 4 are included, the results are virtually the same, indicating that whether workers have moved outside of Beijing does not significantly change the impact of external learning on problem-solving ability. Column 5 of table 4 reports the results when both interaction terms are included, which is virtually the same as when either one of the interactions is considered. Thus, our concern with spurious finding is not warranted.

In summary, *Location* moderates the contribution of mobility, but not that of external learning. It is also important to note that differences between the impact on inter and intra-regional mobility are not related to fundamental differences in human capital. Sample t-tests show that there are no significant differences in tenure, age, salary (at the 5% significant level), education level, range of skills and the positions of responsibility in the organization between R&D workers with different patterns of mobility.

Our results provide useful comparators to other similar studies of mobility outside China. On the hand - and bearing in mind that we are measuring employee problem-solving in the firm rather than firm performance or labour productivity - in contrast to for example ERIKSSON (2010), who concluded that knowledge flows via labour mobility in Sweden are predominantly a local process, we find mobility overall has a positive and significant effect, irrespective of where this comes from. Two factors may be relevant here. Firstly it may reflect the fact that, unlike Sweden, China has a large and geographically spread Mandarin speaking high-skilled population, which will facilitate communication through language and other cultural aspects with new R&D employees that are recruited from very long distances. Thus the specific geography within which distance may decay the effectiveness of knowledge transfer may vary significantly. CRESCENZI *et al's.*, (2007) suggestion that US firms incorporate labour mobility more easily than firms in Europe would seem to support this. Alternatively, it may also reflect our ICT sector specific study, where skills may be more codified (for example widespread use of software languages), that would facilitate integration of skills across geographical spaces. On the other hand, like ERIKSSON (2010) and BOSCHMA *et al.*, (2009), the results also show that local mobility clearly prevails over mobility that is geographically dispersed. This underlines the importance, in this major Chinese science park, of physical proximity for facilitating the process of absorbing skills and knowledge spillovers in the organization. As MALMBERG and MASKELL (2002) emphasize, the positive effects of co-location and geographical proximity are therefore underlined.

GUANXI RECRUITMENT

The previous section raised the question of whether labour recruitment based on Guanxi networks might violate the assumption that individuals were recruited on a meritocratic basis. It was also discussed that Guanxi-type practices may be more prevalent in Chinese state-owned firms than in non-government owned firms that need to survive in the market. The ownership structure of firms in which R&D employees who participated in the survey is overwhelmingly based on cooperatives. Of 65 firms for whom the information was available, only 3.08% are wholly Chinese state-owned enterprises and almost 78% are cooperatives. In the Chinese context, cooperatives are enterprises where a significant but minority stake is owned by the state, but where management is relatively autonomous and answers to the stakeholders, a majority of which are private individuals (CAI and TYLECOTE, 2005). On this basis it is likely to be run on lines similar to private enterprises and therefore instill more formal open recruitment systems to recruit the best employees. The regression analysis was undertaken to investigate if the form of recruitment impacts problem-solving ability. For this purpose, a dummy variable, *Open-Market*, was incorporated, which reflects relatively open methods of recruitment in the current job. Table 1 gives the detailed description of this variable. It takes a value of 1 if a knowledge worker was recruited in an open labour market form, and 0 if *Guanxi* ties were used. Following the same estimation strategy as previously, we replaced the variable *Location* with *Open-Market* and estimated the direct effect of the means of recruitment on problem-solving as well as its moderating role on the impact of mobility and external learning. The results are reported in column 6 to 9 of Table 4. It shows that the form of recruitment does not influence individual problem-solving directly or indirectly.

Taking into account both the regional pattern of mobility and the means of recruitment together, their contribution to individual problem-solving was re-estimated and the results are presented in column 10 to column 15 of Table 4. It again confirms that *Location* does negatively moderate the impact of mobility, while the means of recruitment do not influence the workers' problem-solving ability.

Across all specifications *Education* is insignificant, and *Seniority* is marginally significant and positive except for two cases (column 13 and 15). In comparison with the results in column 1, both *Log(tenure)* and *Log(experience)* lose significance. Given that this subsample of workers is characterized by being more mobile, it is less surprising that tenure is not a major factor in their problem-solving capability. However, we would have expected *Log(Experience)* to have retained significance, although significance may be hard to identify if there is little variance in either tenure and experience across this relatively small sample of mobile workers.

ACCESSING PROFESSIONAL NETWORKS

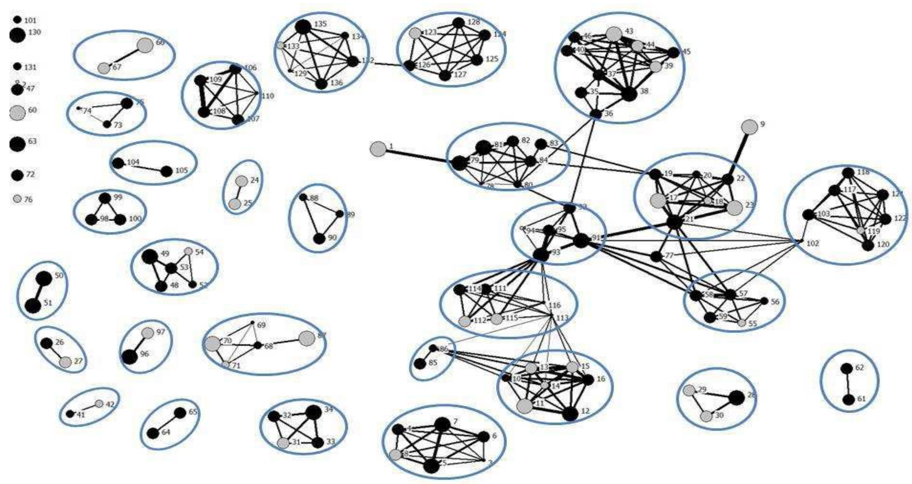
From the results presented in table 4, the conclusion is reached that localized mobility is more conducive to R&D workers problem-solving ability than mobility across regions. We also find that differences in the form of recruitment between employees with work career histories within and outside of the ZGC Park do not appear to account for these differences. In the following section we investigate another possible explanation, whether diverse regional patterns of mobility might influence the nature of employee career networks and hence access to knowledge.

Studies linking mobility and careers of scientists and engineers to knowledge flows can be traced back to GRANOVETTER's (1974) studies on job search amongst professional, technical and managerial workers. This work emphasized that mobility of individuals can tell us a great deal about the relationships firms actually maintain with each other. The significance of inter-firm linkages in this case is that links established via job mobility are not only likely to increase the competitiveness of individual firms, it might also be a key ingredient for the emergence of localized business systems. This is because mobility between workplaces generates "weak" occupational ties (GRANOVETTER, 1973; AGRAWAL *et al.,* 2006), which creates social cohesion between firms exchanging personnel. Other work in this vein emphasizes the importance of building social capital alongside strong networks (DEFILLIPPI *et al.,* 2006; BROWN and DUGUID, 2001) and the building of common practices for learning within different types of practitioner groups (LISSONI, 2001; WELZ, 2003). It is furthermore argued that, given the importance of fluid communication for the transfer of tacit and often highly complex knowledge, physical proximity will underline the benefits of these informal associations, hence many examples of knowledge worker ties emerge from studies of spatially clustered firms such as Silicon Valley (SAXENIAN, 1994) and the Cambridge and Munich science clusters (CASPER and MURRAY, 2005). Establishment of a wide network of "local" ties around common practices may therefore be crucial in instituting fluid lines of communication and may also lower some of the transaction costs associated with building practitioner networks (ERIKSSON and LINDGREN, 2009). Local networks can therefore be interpreted as underpinned by common learning routines, but also by informal institutions that strongly influence how these networks function (for example around issues of openness, tacit agreements for the sharing of knowledge etc). Nevertheless, it is also important to note that while there is reasonably extensive evidence that proximity to labour market skills positively impacts firm performance, there is less widespread evidence that the existence of practitioner networks has the same effect.

To investigate this question empirically we can refer to CASPER and MURRAY (2005), who argued that engineers and scientists are assumed to have established a link (or an edge) if they have worked in the same institution at some point. A network is therefore formed if two individuals are linked by a common career history i.e. an individual has worked in one place and then moved to another, but is still assumed to retain a link with a previous workplace. We can then argue that if R&D employees that have had career movements only in Beijing have on average stronger ties than those coming from outside the Park, it would suggest a reason for why the impact of labour mobility is different.

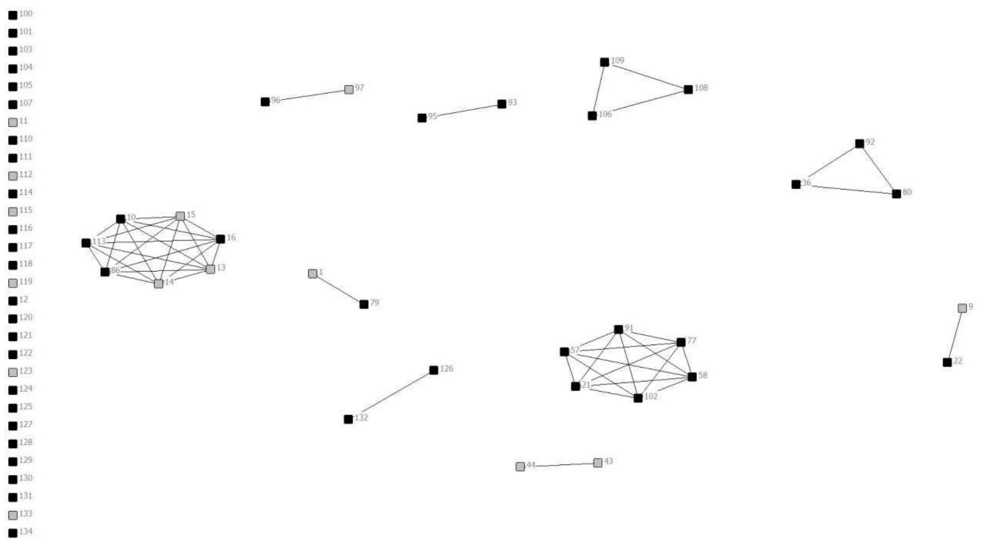
This is done by tracing career histories of 131 out of 314 managers and R&D employees that provided this data to create one-mode networks that establish ties between R&D employees on the basis of common prior employment affliction. Previous workplaces were differentiated by categorizing them into two categories ("inside ZGC Park = 1", "outside ZGC Park = 2"). Figure 2 presents the network visualizations of the complete networks using UCINET social network analysis software. The thickness of the ties represents the shared affiliations and social connections between two R&D employees. The black nodes represent the R&D employees that have only changed their jobs inside ZGC Park; the grey nodes represents those that have been working outside the ZGC Park. In figure 2, ties within the existing organizations are shown within each circle i.e. individuals in each circle work in the same organization. However, given our interest in studying whether geographically dispersed or concentrated patterns of "past" career affiliation influence the ability of individuals to establish networks of collaboration, the relevant lines are those that link different circles.

Figure 2
Network analysis of career links between R&D employees (including current workplaces)



The network map shows few common career points of tangency with other workers, suggesting few networks are formed through past career affiliation in our sample. Figure 3 illustrates more clearly the number of links knowledge workers have with others, this time not including current workplaces. The results show that with the exception of two small clusters, there exist very sparse career networks between R&D workers in the ZGC park. Few appear to have moved jobs together or to have established a common link within for example a dominant employing organization. Perhaps more significantly, there isn't a clear difference in networking pattern between those that have moved jobs outside and inside the ZGC Science Park.

Figure 3
Network analysis of career links between R&D employees (not including current workplaces)



A more formal way of quantifying differences in network access between R&D employees with careers histories inside and outside the ZGC Park is to compare indicators of centrality. Centrality is one of the most important and widely used tools in social network analysis for it identifies the most important actors within the network (CARRINGTON *et al.*, 2005). Social network analysis proxies "importance" by the position of actors (or nodes) in a network, the assumption being that actors in the centre of networks will have greater access to knowledge, therefore will be able to make better informed decisions more quickly (EVERETT and BORGATTI, 2005) or will be strategically placed to better exploit entrepreneurial opportunities (BURT, 2005). Alternative measures of centrality have therefore evolved to capture the importance of actors in a network. Here, we suggest that individuals that have established a greater number of local links with ex-colleagues in previous workplaces may be in better position to access relevant information and knowledge and to do this more quickly. For this reason, and due to nature of our data, we use *degree* centrality. This can be defined as the number of ties incident upon a node or the number of paths of length that emanate from a node

(EVERETT and BORGATTI, 2005). Degree centrality therefore is a relatively basic measure of the number of links each actor has in the network.

Table 5 below compares the degree centrality between knowledge workers with a history of mobility only in the ZGC Park (group 1) with those that reported some previous jobs outside the Park (group 2). The results show there is no significant difference in the mean centrality between group 1 and group 2 (0.778 and 0.676), which confirms the earlier diagrammatical representation that the differences in performance alluded to earlier in the paper are unlikely to be explained by networking insertion or access to effective networks.

Table 5

Average of "betweenness centrality" - Inside ZGC Park VS Outside ZGC Park (including current workplaces)

		Inside ZGC Park (Group 1)	Outside ZGC Park (Group 2)
Degree Centrality	Mean	0.778	0.676
	Max	7	7

CONCLUSIONS

The evidence presented in this paper highlights that mobility positively contributes to the problem-solving ability of R&D workers in innovation projects in ICT firms in this major Chinese Science Park, although this impact is heightened when mobility is local and geographically concentrated. This result remains robust despite controlling for a number of generic human capital variables that reflect skills and experience gained within and outside of the organization.

The significance of this finding is that it suggests that local mobility and recruitment of high-skilled individuals is a factor in the development of agglomeration economies. CRESCENZI (2005) argued that the manner in which knowledge is transmitted, its degree of cumulativeness and complementarities will affect the degree to which spillovers are produced and can help explain regionally differentiated development patterns. Thus, while previous research has emphasized that knowledge flows can be highly reliant on people taking tacit knowledge with them (ALMEIDA and KOGUT, 1999) and indeed that beyond labour supply, matching between labour demand and education skills is critical for growth (RODRIGUEZ-POSE and VILALTA-BUFI, 2005), we suggest this process has a spatial dimension, underlined by the interdependencies that exist between skills, local institutions and firm capabilities or routines.

However, an important point also raised in the discussion relates to the difficulties that exist in pinpointing the factors that account for this local effect. Aside from generic human capital characteristics that were largely consistent across R&D employees with different patterns of spatial mobility, it was also found that the methods and forms of recruitment of individuals, that may have been different in China compared to Western European firms, did not appear to influence the relationship between problem-solving ability and mobility. Preferential access to career networks also did not appear to differentiate R&D employees, which would suggest that the link between mobility and professional networks, as strongly emphasized by for example SAXENIAN (1994), is not a major factor in our limited sample study of Zhongguancun.

By contrast, studies that emphasize cognitive matching of competencies between individuals and firms at a local level suggest a coherent explanation. The advantages that some R&D workers may have in applying their knowledge, will be related to complementarities developed with local firms, but that these are at least in part drawn from common knowledge and familiarity with cultural and institutional contexts developed in the region. Such an explanation would tie in with for example BOSCHMA *et al.*, (2009) who have argued that routines of firms within a sector can be more similar within a region than across them.

In terms of the broader conclusions that can be drawn from these results, clusters are notoriously diverse and rely on locally built institutions that are difficult to imitate, therefore generalizing from single cluster studies is hazardous. Nevertheless, our finding is consistent with the concept of building agglomeration economies through the intertwining of local institutions, hence the importance of local mobility is unlikely to be a strictly Chinese phenomena. However, insofar as Zhongguancun represents a leading high-technology cluster in China, comparisons with leading clusters in other countries might usefully rely less on the ability to build agglomeration economies which would be expected, than on the ability to absorb outside knowledge and adapt to changing technologies. As RODRIGUEZ-POSE and CRESCENZI

(2008) argue, knowledge flows are geographically bounded and distance can bring a decay effect, therefore efforts are needed to improve absorptive effects. CRESCENZI *et al.*, (2007) found that the greater ability of US firms to benefit from migration (and hence greater diversity of knowledge flows) in part comes down to the greater absorptive capability of US firms compared to Europe. Whilst we would therefore expect the importance of local knowledge found in this Chinese study of a predominantly ICT cluster to be replicated across other clusters, we might find much variety in the ability to absorb outside knowledge in the form of skills.

In terms of future work in this area, the limited sample size of this study means that the conclusions from this study would benefit from replication with a larger sample of employees working in the Science Park and in particular beyond the ICT to observe the importance of industry effects for the study of mobility. However, it would also be important to gauge whether the positive effect of local mobility is more generally based on the co-location of knowledge between firms and employees in a region, or rather *where* the knowledge has been formed, including the history of the location. Hence, it may be the case that the positive effect of local mobility will not be replicated in all clusters across China. This would require a comparative empirical study across a number of the Chinese science parks.

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Table 4 Summary statistics for regression variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Coefficient															
Log(Tenure)	0.286*	0.123	0.160	0.125	0.160	0.141	0.157	0.149	0.165	0.140	0.172	0.136	0.154	0.149	0.186
	(0.159)	(0.191)	(0.189)	(0.193)	(0.188)	(0.183)	(0.182)	(0.191)	(0.190)	(0.182)	(0.181)	(0.185)	(0.179)	(0.191)	(0.186)
Log(Experience)	0.164*	0.073	0.105	0.070	0.099	0.083	0.066	0.086	0.069	0.083	0.112	0.077	0.065	0.086	0.102
	(0.085)	(0.159)	(0.152)	(0.161)	(0.153)	(0.163)	(0.165)	(0.165)	(0.168)	(0.161)	(0.155)	(0.165)	(0.163)	(0.164)	(0.162)
Education	0.040	-0.371	-0.368	-0.356	-0.344	-0.343	-0.283	-0.349	-0.289	-0.339	-0.344	-0.336	-0.274	-0.349	-0.324
	(0.271)	(0.488)	(0.482)	(0.498)	(0.495)	(0.474)	(0.491)	(0.470)	(0.488)	(0.482)	(0.483)	(0.493)	(0.500)	(0.479)	(0.524)
Seniority	0.518*	0.910*	0.921*	0.884*	0.886*	0.907*	0.873*	0.919*	0.886*	0.902*	0.914*	0.880*	0.861	0.920*	0.903
	(0.279)	(0.521)	(0.530)	(0.519)	(0.528)	(0.483)	(0.490)	(0.485)	(0.492)	(0.518)	(0.528)	(0.517)	(0.531)	(0.521)	(0.557)
Mobility	0.572***	0.668***	1.179***	0.667***	1.171***	0.666***	0.396	0.676***	0.408	0.663***	1.173***	0.665***	0.386	0.676***	1.083**
	(0.171)	(0.197)	(0.324)	(0.208)	(0.317)	(0.190)	(0.290)	(0.194)	(0.298)	(0.197)	(0.326)	(0.207)	(0.321)	(0.202)	(0.450)
Internal-Learning	-0.050	-0.240	-0.317	-0.210	-0.288	-0.242	-0.248	-0.240	-0.245	-0.243	-0.318	-0.213	-0.250	-0.240	-0.283
	(0.125)	(0.184)	(0.201)	(0.186)	(0.207)	(0.185)	(0.187)	(0.183)	(0.184)	(0.185)	(0.201)	(0.187)	(0.186)	(0.182)	(0.203)
External-Learning	0.417***	0.487**	0.575**	0.333	0.426*	0.477**	0.496**	0.371	0.393	0.478**	0.568**	0.332	0.498**	0.371	0.246
	(0.120)	(0.200)	(0.228)	(0.225)	(0.257)	(0.198)	(0.202)	(0.313)	(0.314)	(0.199)	(0.229)	(0.223)	(0.204)	(0.308)	(0.305)
Selection	-0.554														
	(0.348)														
Location		0.025	2.250**	0.131	2.327**					0.031	2.250**	0.132	0.068	-0.002	2.278**
		(0.502)	(0.912)	(0.498)	(0.930)					(0.507)	(0.925)	(0.501)	(0.522)	(0.498)	(0.931)
Location× Mobility			-1.282***		-1.273***						-1.278***				-1.269***
			(0.422)		(0.432)						(0.426)				(0.464)
Location× External-Learning				0.569	0.529							0.554			0.545
				(0.432)	(0.360)							(0.437)			(0.353)
Open-Market						0.191	-0.439	0.227	-0.399	0.192	0.137	0.118	-0.447	0.227	-0.125
						(0.371)	(0.791)	(0.383)	(0.803)	(0.372)	(0.384)	(0.380)	(0.803)	(0.382)	(0.695)
Opem-Market × Mobility							0.410		0.408				0.417		0.162
							(0.390)		(0.391)				(0.410)		(0.361)
Open-Market × External-Learning								0.159	0.153					0.159	0.268
								(0.387)	(0.386)					(0.374)	(0.331)
κ_1	-2.261***	-1.720***	-1.079**	-1.738***	-1.106**	-1.574***	-1.997***	-1.519***	-1.939**	-1.571***	-0.977**	-1.645***	-1.996***	-1.519***	-1.131
	(0.314)	(0.409)	(0.471)	(0.419)	(0.469)	(0.483)	(0.729)	(0.508)	(0.758)	(0.478)	(0.488)	(0.493)	(0.725)	(0.507)	(0.735)
κ_2	-0.314	0.133	0.835*	0.119	0.804*	0.281	-0.144	0.336	-0.086	0.284	0.939**	0.213	-0.144	0.336	0.773
	(0.260)	(0.366)	(0.467)	(0.383)	(0.462)	(0.452)	(0.695)	(0.484)	(0.729)	(0.447)	(0.472)	(0.466)	(0.694)	(0.483)	(0.729)
κ_3	2.191***	3.093***	3.945***	3.120***	3.966***	3.241***	2.833***	3.302***	2.895***	3.245***	4.050***	3.214***	2.834***	3.302***	3.953***
	(0.248)	(0.383)	(0.490)	(0.411)	(0.496)	(0.499)	(0.645)	(0.554)	(0.704)	(0.494)	(0.475)	(0.517)	(0.639)	(0.553)	(0.705)
Observations	314	122	122	122	122	122	122	122	122	122	122	122	122	122	122

Robust standard errors in parentheses are adjusted for the firms that R&D employees s are working for; *** p<0.01, ** p<0.05, * p<0.1.

[1] Interestingly, Lin's (1990) subsequent social resource theory suggests these weak ties are also mechanisms used to maintain status and hierarchical rank in society.

[2] According to an unpublished report on the development of ZGC, 28.8 per cent of employees (not limited to R&D employees) in ZGC have worked less than one year in their current employment in 2006. In our sample, 30.2 per cent of knowledge workers have a less than one year experience in their current position. This lends some confidence to the representativeness of our sample. Unfortunately, we have no way to tell exactly how serious the selection bias is, because detailed demographical information (i.e., education level, mobility history and working experience) on knowledge workers in ZGC areas in general is not available.

[3] Self-reported dependent variable is used and has been used extensively in innovation research. To name a few, Li and Atuahene-Gima (2001) used self-reported items to measure new technology ventures' performance. Jasen et al. (2005) measure both potential and realized absorptive capacity with self-reported items.