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# Innovation, R&D cooperation and labor recruitment: evidence from Finland

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**Abstract** This article investigates the role played by one type of firm interaction, namely R&D cooperation, and also the acquisition of labor, in the promotion of industrial innovations. We employ a unique innovation dataset from Finland which combines firm specific information about the innovation performance of the firms along with their individual characteristics, as well as firm specific information regarding the origins of their recent labor acquisitions. Analyzing this data allows us to identify the different roles which the knowledge spillovers and labor markets play in the innovation process. Our results suggest that small firms are generally more innovative than large firms; R&D cooperation is an essential feature of innovation, but the variety of cooperation is of little importance; and labor acquisition appears to be only of limited importance for innovation.

**Keywords** Innovation · Labor · Cooperation · R&D

**JEL Classifications** O31 · J60 · L26

## 1 Introduction

Finland is interesting as a benchmark case for analyzing the process of high-technology innovation. This is because it is one of the world's most specialized countries in terms of high technology outputs (Ali-Yrkkö 2001), with one of the highest national R&D to GDP ratios, as well as one of the world's most sophisticated systems of university–industry collaboration (GIER 2006). In addition to these interesting structural features, Finland has also developed uniquely by detailed data on the operation of high technology industries, thereby allowing researchers to investigate analytical issues which are currently not possible in many other countries. This article will employ such unique data in order to investigate the diverse mechanisms by which knowledge spillovers and knowledge transfers may promote different types of innovation.

Over the last two decades, the role played by knowledge spillovers and human capital has become a major focus of research interest amongst economists analyzing processes of innovation and growth. This research interest in knowledge spillovers arose primarily on the basis of the seminal work of Romer (1987), while the role of human capital was highlighted by Lucas (1988). Since then, various extensions and applications of the links between innovation and growth have also been proposed by among others, Acs and Audrestch (1990, 1991) and Porter (1990). In all of these various approaches, knowledge flows are assumed to take place among firms or between firms and organizations, via either knowledge spillovers among individual people, or knowledge transfers via the acquisition of embodied human capital

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(Audrestch and Stephan 1996; Caniels 2000; Breschi and Lissoni 2001a, b). Both of these knowledge transfer mechanisms, namely knowledge spillovers or the acquisition of embodied human capital, are assumed to be mediated primarily by face-to-face contact. However, the relative importance of these different mechanisms has hardly ever been tested.

This article will explicitly examine these questions by identifying and distinguishing between the effects on innovation of knowledge transfers via inter-firm and inter-organizational contacts, from the effects on innovation of knowledge transfers associated with labor acquisition. In order to do this, we employ a unique innovation dataset from Finland on firm innovation behavior, which combines firm-specific information on the nature of inter-firm and inter-organizational contacts, and also the patterns of firm labor recruitment. By relating each of these features to innovation performance we are able to distinguish between the effects on innovation of face-to-face knowledge spillovers from those of labor acquisition. Our results suggest that small firms are generally more innovative than large firms; R&D cooperation rather than R&D is an essential feature of innovation; the variety of cooperation linkages is of little importance for innovation; and labor acquisition appears to be only of limited importance for innovation.

The article is organized as follows. In the next section we provide a brief overview of the key theoretical features of the relationship between innovation, face-to-face interaction and labor markets. In Sect. 3, we discuss the data employed and our methodology. In Sect. 4, we report and discuss the empirical results of our nine different probit models of innovation, with Sect. 5 providing some brief conclusions.

## 2 Knowledge spillovers and innovation

Since the seminal work of Schumpeter (1934), the wide-ranging literature on the determinants of innovation has tended to focus on two key lines of enquiry. First, research aims to identify the characteristics of the firms and entrepreneurs which promote innovation. Here, some of the key issues which have emerged as playing a significant role in promoting firm innovation are the size of the firm and levels of R&D expenditure (Van Dijk et al. 1997), the stock of human capital inputs, the sector of activity, and the mode of firm ownership and organization (Cantwell and Iammarino 2003). More recently, over the last two decades there has also emerged a widespread interest in the role which knowledge spillovers may also play in the innovation process. Among the various approaches employed to identify the nature of these knowledge spillovers, some articles have focused on the role played by specialist labor pools (Audretsch and Stephan 1996; Almeida and Kogut 1999) and the density of local activity (Ciccone and Hall 1996; Carlino et al. 2007) in promoting innovation and growth.

In almost all of the literature dealing with innovation and growth, it is generally assumed that face-to-face contact between individuals and firms is positively related to the levels of innovation. Face-to-face contact might promote innovation by: increasing the possibility of informal knowledge spillovers between firms or individuals; by increasing the mutual transparency of competitor behavior and thereby competitor responses (Porter 1990); by increasing the levels of trust and cooperation between firms (Scott 1988); and by increasing the inter-firm mobility of labor (Almeida and Kogut 1999). In principle, it is theoretically possible to treat the first three knowledge transfer mechanisms as being qualitatively quite similar to each other, whereas the fourth mechanism, namely the inter-firm mobility of labor, is rather different. The reason for this becomes clear if we adopt the analogy of a simple stock-inventory model. The first three types of mechanisms generally involve high-frequency short-term transactions of relatively small quantities of knowledge or information, in comparison to the total knowledge of the persons undertaking the transaction, whereas the inter-firm mobility and acquisition of labor involves relatively less frequent transactions in which the whole human capital of the individual is transferred for a significant period. Unfortunately, a lack of appropriate data has meant that it has previously not been possible to distinguish among these effects. This is because, while empirical data on patents and R&D are readily accessible along with aggregate measures of labor skills and education, additional micro-econometric data on labor mobility and innovation is relatively very difficult to find.

Along with indices of innovation and R&D, a few research articles also have incorporated information on labor hiring patterns. From these articles, there is some evidence which supports the role played by the pools of human capital in promoting innovation (Angel 1991; Audrestch and Stephan 1996; Almeida and Kogut 1999; Breschi and Lissoni 2003; Franco and Filson 2000; Persson 2002; Power and Lundmark 2004). Yet, without very detailed data on both knowledge spillovers and labor mobility, as well as data on innovation, identifying the exact mechanism by which knowledge spillover effects are mediated is very difficult. Moreover, these articles are very much in the minority. As such, there are as-yet been made no comprehensive attempts at distinguishing, isolating, and evaluating the effects of knowledge spillovers which accrue because of inter-firm or inter-organizational relations, from the effects of knowledge transfers embodied in acquired human-capital, which take place due to the mobility of labor among firms. In most recent studies of innovation, analyses which emphasize the role played by informal knowledge spillovers (Kaiser 2002) have tended to predominate over human capital and labor mobility explanations.

In this article, we explicitly aim to identify the role which labor acquisition plays in promoting innovation, after controlling for other firm specific characteristics, including face-to-face contact with other firms and organizations. In order to do this, we employ data on the innovation behavior and performance of Finnish high technology firms. As well as information about the innovation behavior of the firm, these data provide us with detailed information about the structural characteristics of the firms, and also information about the R&D cooperation behavior between individual Finnish firms and organizations.

R&D cooperative relationships usually begin as a result of informal knowledge spillovers, although they subsequently develop into much more complex and formal arrangements. Of all the possible types of inter-firm relations, R&D cooperation relationships require the most intense face-to-face contact in order to be both established and maintained (De Meyer 1993). This is because the required level of trust embedded in the mutual commitments made by the firms tends to be the highest of all types of inter-firm and inter-organizational relations. Therefore, testing whether the existence, nature and variety of R&D cooperation relationships is related to innovation, provides an indirect test of whether the existence, nature and variety of intense and continuing face-to-face contact is related to innovation.

Having controlled for the impact on innovation of a firm's structural characteristics, and also for the nature and variety of a firm's cooperative R&D relationships, we are then also able to extend the argument to investigate the effects on a firm's innovation performance of the origins of the firm's labor acquisitions. This will allow us to isolate the independent role on innovation performance which is played by knowledge transfers associated with human-capital acquisition, from the role associated with inter-firm and inter-organizational knowledge spillovers, associated with R&D cooperation relationships.

In essence, the analysis here attempts to answer the following question: having controlled for all firm scale characteristics, what roles, if any, do R&D cooperation and labor acquisition play in promoting innovation?

## 3 Data and methodology

The establishment-level data used for our research comes from innovation surveys conducted by Statistics Finland in 1996 and 2000. Statistics Finland is the national statistics office for the government of Finland. The innovation surveys undertaken by Statistics Finland are conducted in line with the European Union Community Innovation Survey (CIS) framework and the OECD (2005) definitions and classifications of innovation.[1] These surveys collect information about an individual establishment's innovation performance, defined as the launching of any new or substantially-improved products or processes during the previous two years. In addition to the innovation outputs, the innovation surveys also provide information about the firm's innovation cooperation with other enterprises or

[1] The definitions of innovation are based on the *Oslo Manual* (OECD 2005) which sets out the guidelines for collecting interpreting innovation data from the CIS surveys. All high technology firms did not necessarily take part in all the innovation surveys, which means that the size of data varies from year to year. However, the high technology industries were selected specifically according to the OECD classification. Although the surveys have been conducted every second year from 1996 onwards, at the time of the analysis only the 1996 and 2000 surveys collected detailed information regarding the types of R&D cooperation relationships.

institutions. For the purposes of this research, these innovation databases have also been further expanded with information from the Finnish R&D Surveys, the Finnish Business Register for 1990–2002, and the Finnish Longitudinal Employer-Employee Database (FLEED) maintained by Statistics Finland. These additional databases provide us with information about the R&D expenditure of the firms and also details about the origins of the labor recently acquired by the establishment. Our combined database now includes establishment-level information regarding each of the types of innovations exhibited by an establishment, the employment size of each establishment, the R&D expenditures of the establishment, and the sales revenue of each establishment, the nature and variety of the R&D cooperation relations of the firm, and the origins of the labor recently acquired by the firm.

Our dataset comprise all the Finnish high-technology firms which were included in the two innovation surveys of 1996 and 2000, and are made up of firms engaged variously in biotechnology, electronics, nanotechnology, telecommunications and computers, and activities related to these core technology sectors.

The basic establishment-level unit of analysis we adopt is that of the 'local unit' LU, which contains all of a firm's establishments within the same local municipality, and the innovation behavior we ascribe to the local unit comes from the firm level innovation data. Assigning innovation behavior to the local unit is straightforward in the case of a single plant or single site firm, or a multiple site firm with all establishments in the same locality, because here the firm is the local unit. In the case of a multiplant firm which has establishments in different areas, each individual establishment is the unit of analysis, and in the absence of any additional information, the innovation behavior we ascribe to each establishment is that of the multiplant firm as a whole. In the case of Finnish data this technique has already been previously adopted elsewhere (Alanen et al. 2000).[2] The surveys also provide information about the R&D interaction between individual firms and other firms or institutions, which are specifically undertaken in order to promote innovation, and this information is provided at the level of the firm. Once again, with single plant firms or with multiplant firms in the same locality, assigning interaction and cooperation behavior to the local unit is straightforward. However, in the case of multiplant firms with establishments in different localities, it is possible that all the individual establishments do not interact with other firms or organizations to the same extent. However, once again, in the absence of any additional information, we assign the same levels of cooperation and interaction to each establishment within the same firm.

Given the types of data that we have at our disposal, the analysis of these data is most appropriately undertaken by employing a series of probit models, in which we estimate the probability of a particular type of innovation taking place, as a function of the size and expenditure characteristics of the firm, the cooperation behavior of the firm, and the labor acquisition behavior of the firm. In order to test the relationship between innovation behavior and the importance of these various features, we estimate three different types of probit models. In each of these three models the binary dependent variable is defined as being equal to 1 if the local establishment has managed to introduce new innovations during the previous two years and equal to 0 if it has not. The three separate probit models cover all three response categories of innovations, i.e., product innovations, process innovations, and new products introduced to the market. Product innovation represents the situation where a firm has introduced a product to the market which is new for the particular firm, but not for the industry. Process innovation represents a situation where a firm has introduced a new production process or a new service delivery process. New product to market represents a situation where a firm introduces a product which is new to the market as whole, and can be considered as being the most advanced form of innovation.

The set of independent variables we employ includes dummy variables for the employment size-band categories of the local establishments, continuous variables for the establishment turnover and the lagged R&D expenditures of the establishment, plus a dummy variable indicating whether the establishment has cooperated with other firms and

[2] There are two major justifications for this technique. First, if we assume that information is transferred effectively between different local units within the same firm (Orlando 2000), then it is appropriate to give the same innovation status to all the individual local units of the same firm. Second, the majority of the surveyed firms had less than three establishments, and almost half had only one establishment.

institutions on R&D issues during the previous two years. Our co-cooperation variable takes a value of 1 if the local establishment cooperates with at least one type of partner, and 0 if it does not have any kind of cooperation relationship with external partners. As we have seen in Sect. 2, the importance of the cooperation dummy variable employed here lies in the fact that inter-firm cooperation is generally regarded as being positively related to the level of face-to-face interaction between firms, because of the need to build up mutual trust and confidence. This variable is therefore employed as proxy for face-to-face contact. In terms of labor market variables we employ a continuous variable representing the population density of the region, in order to capture any local externality spillover effects which are external to the individual firm (Carlino et al. 2007). Finally, we employ detailed data about the numbers and also the respective origins of the firm's labor inputs which have been acquired during the previous two years from other sources. This allows us to construct a continuous variable which represents the proportion of a firm's total employment that has been recently acquired from each particular source of human capital.

We run the set of three probit models, Model 1, Model 2, and Model 3, in three different circumstances, giving a total of nine different probit models. The models are estimated on the basis of a pooled dataset from the two survey years of 1996 and 2000. Model 1 estimates the likelihood of a firm producing a product innovation, Model 2 estimates the likelihood of a firm producing a process innovation, and Model 3 estimates the likelihood of a firm producing a new product to market innovation. In the first case we test whether firm innovation performance is related to the existence of either R&D cooperation relations, or to the particular sources of the labor acquired. In the second case we test whether the variety of R&D cooperation relations exhibited by a firm are related to innovation, after controlling for the particular sources of the labor acquired. In the third case, whether the types of R&D cooperation relations exhibited by a firm have any impact on innovation, while controlling for the sources of the labor acquired. As such, our models become progressively more detailed as we move from the three first-stage models to the three third-stage models.

## 4 Results and discussion

The raw non-adjusted data (McCann and Simonen 2005) show that between the different size bands, the proportion of firms innovating is relatively high among both the groups of very small local establishments employing less than 10 people, and also the larger establishments employing more than 50 people, whereas the probability of innovation appears to be lower among the establishments employing between 10 and 49 people. This gives rise to a J-shaped relationship between establishment size and innovation intensity as observed by Tether et al. (1997). A similar pattern is also observed for the probability of cooperation for R&D activities. However, without also controlling for the various firm characteristics within a probit model framework, these preliminary observations cannot be relied on as being robust.

The nine estimated probit models reported in Tables 1, 2, and 6 have a goodness-of-fit of between 0.216 and 0.514,[3] and with all models exhibiting an increasing goodness-of-fit with the inclusion of additional explanatory variables. Moreover, as we see in Tables 3–5, the prediction performance of the models is consistently very high with the various models correctly predicting the observed outcomes in between 71% and 86% of the observed cases. The threshold predictive value for accepting the predictive performance of each of the models is when 50% of observations are correctly predicted, so all of the models easily surpass this acceptance criterion.[4]

[3] McFadden (1979) and Louviere et al. (2000) argue that for categorical response variable models, a McFadden pseudo $R$-squared value of between 0.2 and 0.4 represents a very good fit, with a pseudo $R$-squared value of 0.2 corresponding to an OLS $R$-square value of the order of 0.7. In addition, we also report the Efron pseudo $R$ squared statistic, which is not based on maximum likelihood estimations, but rather on the first and second moments of the actual and fitted values (Estrella 1998).

[4] In order to check the robustness of the results we also estimated the various models using logit models, and the results are more or less identical to those generated by the probit models. In addition we report the prediction tables (Tables 3–5), which use the estimated coefficients, apply them to each individual observation in the original data, and then count the number of correctly observed outcomes. As we see, almost all individual 1 or 0 counts pass the threshold value, and the models as a whole easily surpass the 50% correct prediction criterion.

**Table 1** The probit model: likelihood of introducing innovations as a function of R&D cooperation and labor acquisition

| Dependent variable (0,1) | The introduction of product innovation | | The introduction of process innovation | | The introduction of new products to the market | |
|---|---|---|---|---|---|---|
| The name of the explanatory variables | The coefficients of Model 1 (*p*-values in parenthesis) | | The coefficients of Model 2 (*p*-values in parenthesis) | | The coefficients of Model 3 (*p*-values in parenthesis) | |
| Intercept/Constant | −9.8810*** | (0.0011) | 3.4295 | (0.1716) | −3.0377 | (0.2359) |
| Categories of LUs | | | | | | |
| Very small LUs (1–9) | 2.8666*** | (0.0039) | −0.8018 | (0.3680) | 2.2207** | (0.0406) |
| Small LUs (10–19) | 2.5989*** | (0.0008) | −1.9092*** | (0.0052) | 1.1918* | (0.0791) |
| SMLUs (20–49) | 1.6072** | (0.0106) | −1.2571** | (0.0346) | 1.0366* | (0.0816) |
| SMLUs (50–99) | 0.7570 | (0.1722) | −1.3680** | (0.0132) | 0.7792 | (0.1561) |
| SMLUs (100–249) | 0.4476 | (0.3621) | −0.9578** | (0.0243) | 0.9708** | (0.0399) |
| Large LUs (250→) | 0.0000 | *Reference category* | 0.0000 | *Reference category* | 0.0000 | *Reference category* |
| Log sales revenue | 0.6119*** | (0.0003) | 0.0190 | (0.8891) | 0.2007 | (0.1491) |
| Log R&D expenditures (1 year lag) | 0.1166 | (0.1939) | −0.1668** | (0.0315) | 0.0104 | (0.9013) |
| Cooperation | 2.0445*** | (<.0001) | 1.1888*** | (0.0005) | 1.3598 *** | (<.0001) |
| Acquisition of labor (2 year lag) | | | | | | |
| From the same high technology industry | −2.0388 | (0.5029) | −2.2922 | (0.3075) | 1.4506 | (0.5987) |
| From other high technology industry | 0.0823 | (0.9848) | −0.1278 | (0.4940) | 2.5380 | (0.6616) |
| From research centre or university | 6.7623 | (0.2257) | 3.8430 | (0.3647) | 2.2893 | (0.6199) |
| From other industries | 0.3560 | (0.6349) | 0.8152 | (0.5693) | 2.6688 | (0.1906) |
| Students | 0.2070 | (0.8115) | −0.5078 | (0.7081) | 1.2396 | (0.1944) |
| Others (e.g. part-time employees, unemployed) | −2.0188*** | (0.0017) | −1.8886* | (0.0596) | −3.3875*** | (0.0006) |
| Population density | −0.0031*** | (0.0017) | −0.0007 | (0.3883) | −0.0009 | (0.2944) |
| Number of observations | 219 | | 153 | | 151 | |
| Log-likelihood | −62.7593 | | −83.1339 | | −68.5010 | |
| LR-test (diff., df, *p*-value) | 58.43, 17, <.0001 | | 22.89, 17, <.0001 | | 20.67, 17, <.0001 | |
| McFadden's likelihood ratio index | 0.482 | | 0.216 | | 0.232 | |
| Efron's pseudo $R^2$ fit measure | 0.507 | | 0.261 | | 0.274 | |

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

**Table 2** The probit model: likelihood of introducing innovations as a function of the variety of R&D cooperation

| Dependent variable (0,1) | The introduction of product innovation | | The introduction of process innovation | | The introduction of new products to the market | |
|---|---|---|---|---|---|---|
| The name of the explanatory variables | The coefficients of Model 1 (*p*-values in parenthesis) | | The coefficients of Model 2 (*p*-values in parenthesis) | | The coefficients of Model 3 (*p*-values in parenthesis) | |
| Intercept/Constant | −10.3889*** | (0.0009) | 3.8264 | (0.1385) | −2.8546 | (0.2617) |
| Categories of LUs | | | | | | |
| Very small LUs (1–9) | 3.1230*** | (0.0025) | −0.5847 | (0.5273) | 2.3005** | (0.0334) |
| Small LUs (10–19) | 2.8946*** | (0.0004) | −1.7906*** | (0.0100) | 1.2883* | (0.0609) |
| SMLUs (20–49) | 1.8758*** | (0.0048) | −1.0691* | (0.0823) | 1.1571* | (0.0571) |
| SMLUs (50–99) | 0.8853 | (0.1236) | −1.3606** | (0.0191) | 0.8251 | (0.1418) |
| SMLUs (100–249) | 0.4778 | (0.3454) | −1.0022** | (0.0221) | 0.9752** | (0.0400) |
| Large LUs (250→) | 0.0000 | *Reference category* | 0.0000 | *Reference category* | 0.0000 | *Reference category* |
| Log Sales Revenue | 0.6679*** | (0.0002) | 0.0288 | (0.8369) | 0.1995 | (0.1490) |
| Log R&D expenditures (1 year lag) | 0.0996 | (0.2710) | −0.1972** | (0.0168) | 0.0033 | (0.9695) |
| Categories of the wideness of cooperation | | | | | | |
| No partners | −2.3897*** | (<.0001) | −1.5198*** | (<.0001) | −1.5506*** | (<.0001) |
| 1–2 types of partners | −0.6609 | (0.1548) | −0.9280*** | (0.0139) | −0.5126 | (0.1822) |
| 3–4 types of partners | −0.4149 | (0.3530) | −0.1900 | (0.5471) | −0.1049 | (0.7720) |
| 5–7 types of partners | 0.0000 | *Reference category* | 0.0000 | *Reference category* | 0.0000 | *Reference category* |
| Acquisition of labor (2 year lag) | | | | | | |
| From the same high technology industry | −2.5583 | (0.4226) | −2.9237 | (0.2020) | 1.0742 | (0.6966) |
| From other high technology industry | −0.0144 | (0.9972) | −0.7318 | (0.7104) | 2.1593 | (0.6597) |
| From research centre or university | 6.8057 | (0.2217) | 3.1873 | (0.4608) | 2.0884 | (0.6504) |
| From other industries | 0.3768 | (0.6217) | 0.7982 | (0.5880) | 2.6585 | (0.1950) |
| Students | 0.4079 | (0.6464) | −0.2573 | (0.8601) | 1.3453 | (0.1569) |
| Others (e.g. part-time employees or previously unemployed) | −2.0609*** | (0.0017) | −1.7648* | (0.0771) | −3.2323*** | (0.0008) |

**Table 2** continued

| Dependent variable (0,1) | The introduction of product innovation | | The introduction of process innovation | | The introduction of new products to the market | |
|---|---|---|---|---|---|---|
| The name of the explanatory variables | The coefficients of Model 1 (*p*-values in parenthesis) | | The coefficients of Model 2 (*p*-values in parenthesis) | | The coefficients of Model 3 (*p*-values in parenthesis) | |
| Population density | −0.0030*** | (0.0025) | −0.0006 | (0.4797) | −0.0008 | (0.3690) |
| Number of observations | 219 | | 153 | | 151 | |
| Log-likelihood | −61.6742 | | −79.9045 | | −67.6854 | |
| LR-test (diff., df, p-value) | 59.51, 19, <0.001 | | 26.11, 19, <0.001 | | 21.58, 19, 0.001 | |
| McFadden's likelihood ratio index | 0.491 | | 0.246 | | 0.242 | |
| Efron's pseudo $R^2$ fit measure | 0.502 | | 0.284 | | 0.288 | |

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

**Table 3** Predictive performance of models in Table 1

Model 1 in Table 1 (86.3% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Product innovations | 0 | 36 | 17 | 53 |
| | 1 | 13 | 153 | 166 |
| | Total | 49 | 170 | 219 |

Model 2 in Table 1 (70.6% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Process innovations | 0 | 54 | 24 | 78 |
| | 1 | 21 | 54 | 75 |
| | Total | 75 | 78 | 153 |

Model 3 in Table 1 (78.8% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| New products to the market | 0 | 20 | 22 | 42 |
| | 1 | 10 | 99 | 109 |
| | Total | 30 | 121 | 151 |

The threshold value for accepting the predictive performance of each of the models is 0.5

**Table 4** Predictive performance of models in Table 2

Model 1 in Table 2 (85.4% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Product innovations | 0 | 35 | 18 | 53 |
| | 1 | 14 | 152 | 166 |
| | Total | 49 | 170 | 219 |

Model 2 in Table 2 (70.6% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Process innovations | 0 | 52 | 26 | 78 |
| | 1 | 19 | 56 | 75 |
| | Total | 71 | 82 | 153 |

Model 3 in Table 2 (78.8% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| New products to the market | 0 | 20 | 22 | 42 |
| | 1 | 10 | 99 | 109 |
| | Total | 30 | 121 | 151 |

The threshold value for accepting the predictive performance of each of the models is 0.5

**Table 5** Predictive performance of models in Table 6

Model 1 in Table 6 (84.9% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Product innovations | 0 | 34 | 19 | 53 |
| | 1 | 14 | 152 | 166 |
| | Total | 48 | 171 | 219 |

Model 2 in Table 6 (72.5% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| Process innovations | 0 | 56 | 22 | 78 |
| | 1 | 20 | 55 | 75 |
| | Total | 76 | 77 | 153 |

Model 3 in Table 6 (79.5% correct)

| Frequency | | Predicted category 0 | 1 | Total |
|---|---|---|---|---|
| New products to the market | 0 | 19 | 23 | 42 |
| | 1 | 8 | 101 | 109 |
| | Total | 27 | 124 | 151 |

The threshold value for accepting the predictive performance of each of the models is 0.5

**Table 6** The probit model: likelihood of introducing innovations as a function of the types of R&D cooperation

| Dependent variable (0,1) | The introduction of product innovation | | The introduction of process innovation | | The introduction of new products to the market | |
|---|---|---|---|---|---|---|
| The name of the explanatory variables | The coefficients of Model 1 (*p*-values in parenthesis) | | The coefficients of Model 2 (*p*-values in parenthesis) | | The coefficients of Model 3 (*p*-values in parenthesis) | |
| Intercept/Constant | −11.6567*** | (0.0004) | 4.4667* | (0.1011) | −2.4880 | (0.3474) |
| Categories of LUs | | | | | | |
| Very small LUs (1–9) | 3.8580*** | (0.0005) | −0.6604 | (0.4972) | 2.2587** | (0.0361) |
| Small LUs (10–19) | 3.6737*** | (<.0001) | −1.6130** | (0.0249) | 1.5803** | (0.0284) |
| SMLUs (20–49) | 2.5375*** | (0.0009) | −0.9108 | (0.1557) | 1.4332** | (0.0306) |
| SMLUs (50–99) | 1.3449** | (0.0387) | −1.1977** | (0.0375) | 1.1048* | (0.0625) |
| SMLUs (100–249) | 0.7803 | (0.1724) | −1.1764*** | (0.0116) | 1.1112** | (0.0302) |
| Large LUs (250→) | 0.0000 | *Reference category* | 0.0000 | *Reference category* | 0.0000 | *Reference category* |
| Log sales revenue | 0.7519*** | (0.0002) | 0.0489 | (0.7493) | 0.1899 | (0.1980) |
| Log R&D expenditures (1 year lag) | 0.1507 | (0.1345) | −0.2249** | (0.0156) | −0.0028 | (0.9764) |
| Cooperation | | | | | | |
| Within enterprise | 1.7166*** | (0.0005) | 0.6047* | (0.0775) | 1.0631*** | (0.0045) |
| With suppliers | 0.7911* | (0.0732) | 0.4085 | (0.1958) | −0.2452 | (0.4875) |
| With clients or customers | 0.7182* | (0.0987) | 0.0699 | (0.8566) | 0.6410* | (0.1019) |
| With competitors | −0.6963 | (0.1637) | 0.3988 | (0.2311) | 0.1839 | (0.6133) |
| With consultants | 0.1845 | (0.6928) | −0.1137 | (0.7008) | −0.2869 | (0.4159) |
| With universities and higher education institutes | 0.1031 | (0.8271) | −0.1620 | (0.6815) | 0.2759 | (0.4946) |
| With government or private non-profit research institutes | 0.5663 | (0.2783) | 0.9896*** | (0.0023) | 0.0865 | (0.8113) |
| Acquisition of labor (2 year lag): | | | | | | |
| From the same high technology industry | −3.2350 | (0.3701) | −3.7624 | (0.1341) | −0.0887 | (0.9754) |
| From other high technology industry | 1.7229 | (0.7063) | −0.4181 | (0.8405) | 3.3875 | (0.5730) |
| From research centre or university | 7.0037 | (0.2254) | 4.0950 | (0.3741) | 2.7276 | (0.5761) |
| From other industries | 0.3116 | (0.7142) | 0.3649 | (0.8230) | 2.4843 | (0.2516) |
| Students | 1.7974* | (0.0665) | −0.0424 | (0.9794) | 1.8421* | (0.0666) |
| Others (e.g. part-time employees or previously unemployed) | −2.5680*** | (0.0009) | −1.6523 | (0.1603) | −3.2648*** | (0.0014) |
| Population density | −0.0031** | (0.0028) | −0.0003 | (0.7064) | −0.0008 | (0.3913) |

**Table 6** continued

| Dependent variable (0,1) | The introduction of product innovation | The introduction of process innovation | The introduction of new products to the market |
|---|---|---|---|
| The name of the explanatory variables | The coefficients of Model 1 (*p*-values in parenthesis) | The coefficients of Model 2 (*p*-values in parenthesis) | The coefficients of Model 3 (*p*-values in parenthesis) |
| Number of observations | 219 | 153 | 151 |
| Log-likelihood | −58.9113 | −73.6706 | −65.4460 |
| LR-test (diff., df, *p*-value) | 62.28, 29, <0.001 | 32.35, 29, <0.001 | 23.82, 29, 0.016 |
| McFadden's likelihood ratio index | 0.514 | 0.305 | 0.267 |
| Efron's pseudo $R^2$ fit measure | 0.507 | 0.353 | 0.308 |

***Significant at the 1% level; **Significant at the 5% level; *Significant at the 10% level

Table 1 shows the results of the models which test whether innovation is related to either the existence of R&D cooperation relations, or to the origins of the labor acquired. In terms of the various size characteristics of the firm, a small firm employment size below 50 employees appears to be positively and significantly related to the introduction of both product innovations and also to the introduction of new products to market. Meanwhile, all firm sizes between 10 and 249 employees are less likely to exhibit process innovations than are large firms. At the same time, sales revenue is positively and significantly related to new product innovations, while R&D expenditure appears to be negatively related to process innovations.

The one variable which is consistently found to be positively related to all types of innovation performance is R&D cooperation. In these three models, cooperation with other firms or organizations for R&D is always positively and significantly related to all three types of innovation. As we have already mentioned, R&D cooperation relationships require the most intense face-to-face contact in order to be both established and maintained. Therefore, this result supports the argument that face-to-face contact is always essential for all types of innovation.

In terms of the labor market results, we find no support for the argument that population density (Carlino et al. 2007) is important for innovation. Indeed, controlling for the various firm characteristics we find a negative result for product innovations. The only other significant labor market effect at this stage relates to the labor recently acquired which had previously not played a full part in the labor market, such as those who were previously unemployed or part-time workers. Innovation of all three types appears to be negatively related to the proportion of a firm's workers which fall into this category.

Table 2 reports the results of the models which test whether the variety of types of R&D cooperation exhibited by the firm are related to innovation, after controlling for the origins of the labor acquired. The seven types of cooperation partners are: other establishments within the same firm; customers and clients; suppliers; competitors; higher educations institutions; consultants; government research institutes or non-profit private research institutes. The motivation for this model formulation comes from the principles underlying new economic geography which regard the variety of knowledge and input linkages is critical (Fujita et al. 1999).

In terms of the number and variety of R&D cooperation, an absence of R&D cooperation is negatively related to all three types of innovation, in comparison to the benchmark case of 5–7 types of partners, while cooperation with two or fewer types of partners is negatively and significantly related to the likelihood of producing process innovations. For product innovations and process innovations the variety of partners appears to be unrelated to innovation. Meanwhile, the results for firm employment size, sales revenue, R&D expenditure, labor acquisition, and population density are a little changed from before.

Table 6 reports the results of the models which test whether types of origins from where labor is acquired have any impact on innovation, having controlled for the types of R&D cooperation relations exhibited by a firm. Once again, the results for firm turnover, R&D expenditure, and population density remain as above. The results regarding the origins of recently acquired labor also remain largely as above, except that the acquisition of university graduates is now positively related to new product innovations and new products to market.

One feature which emerges clearly now is the increasing advantage of having a small firm size for generating innovations. Controlling for all firm and labor market characteristics, we see that smaller firms are relatively more likely to produce both new product innovations and also new products to market than are the benchmark case of large firms (250+ employees). This is demonstrated both by the increasing values of the significant estimated coefficients as firms sizes fall, and also by the increasing level of significance associated with smaller firm sizes.

In terms of process innovations, very small firms (1–9 employees) are no more likely to produce process innovations than very large firms (250+ employees), although both very large and very small firms are always more likely to produce process innovations than medium sized firms. As such, in terms of generating process innovations, the disadvantages of being a medium sized firm (10–249 employees) are still clearly evident.

In terms of the types of cooperation, R&D cooperation with other parts of the same enterprise is always positively related to all forms innovation. R&D cooperation with customers is only weakly related to product innovation and new products to market, while R&D cooperation with suppliers is weakly related to product innovations. R&D cooperation with government or private non-profit research institutes only appears to be positively related to the introduction of process innovations, while no other forms of R&D cooperation, including that with universities, appear to be significantly related to any type of innovation behavior.

We can summaries these various results into five basic observations.

Our first observation is that controlling for the characteristics of a firm and its external relations, firm smallness increases the likelihood of a firm generating both product innovations and new product to market innovations. This result is broadly consistent with the observations of Brouwer and Kleinknecht (1999).

Our second observation is that R&D cooperation significantly increases the likelihood of all types of innovations. This result differs from the observations of Brouwer and Kleinknecht (1999). However, cooperation between establishments within the same firm enterprise appears to be by far the most important form of cooperation. Cooperation with other firms or organizations only appears to be significant at the 10% level in specific cases, such as with customers for both product innovations and new products to market, with suppliers for product innovations, and with research institutes for process innovations.

Our third observation is that neither the origins of the labor acquired nor the local population density appear to be related to innovation performance.

Our fourth observation is that after controlling for all firm characteristics, R&D expenditure does not appear to be related to either product innovation or new product to market innovations, and is consistently negatively related to process innovations. Presumably this implies that there is competition for resources between R&D and process innovations. On the other hand, cooperation with universities or research institutes may facilitate process innovations. These results are therefore quite different to the findings of Audretsch and Vivarelli (1996).

Our fifth observation is that, contrary to new economic geography assumptions, there is very little evidence that the variety of relations plays any major role in the promotion of innovation. Rather than variety being the dominant aspect of face-to-face contact, it appears that the intensity and continuity of a firm's external relations are paramount. This observation appears to be broadly consistent with the arguments in the Total Quality Management (TQM) literature (Schonberger 1996) which suggest that intense long-term interactions with just a small selected number of firms and individuals can foster the promotion of innovation at all stages in the supply chain (Nishiguchi 1994).

## 5 Conclusions

No previous articles, as far as we are aware, have been able to relate data on both firm R&D cooperation and labor acquisition to different types of innovation in a manner which is as detailed and comprehensive as in this piece of research. By using data on R&D cooperation as a proxy for face-to-face contact and knowledge spillovers, and combining this with information on the sectoral origins of a firm's labor acquisitions, our results begin to shed some light on the knowledge transfer mechanisms via which innovation takes place within Finnish high technology industries. Our results suggest that internal knowledge generation and formal knowledge transfer mechanisms are more important for all types of innovation than external tacit knowledge spillovers. At the same time, we find little or no evidence of innovation being related to the sectoral patterns of labor acquisition, except for the hiring of university graduates, and for the development of process innovations via partnerships with research institutes. Universities appear to play no direct role in the promotion of innovation. That is not to say that external knowledge spillovers are not important for innovation. Rather, in the particular case of the Finnish high-technology sector, our evidence suggests that external tacit knowledge spillovers play a much lesser role than much of the current literature on innovation systems assumes.

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