Innovation strategies, external knowledge and productivity growth

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Abstract

This paper studies firms' capability to recombine internal and local knowledge. It measures the outcome in terms of total productivity growth. Using Swedish data on commuting time for face-to-face contacts across all 290 municipalities, we employ a time sensitive approach for calculating localized knowledge within a municipality and and its close neighbors. Internal knowledge is captured by register data on firms' innovation intensity. The two sources of knowledge are modelled in a production function setting by discrete composite variables with different combinations of input factors. Applying the model on Swedish firm level panel data, we find strong evidence of differences in the capacity to benefit from external knowledge among persistent innovators, temporary innovators and non-innovators. The results are consistent regardless of whether innovation efforts are measured in terms of the frequency of patent applications or the level of R&D investment.

Keywords: Innovation strategies, localized knowledge, patents, TFP growth, panel data

JEL Codes: C23, O31, O32

1 INTRODUCTION

This paper addresses the question of how different levels and combinations of internal and external knowledge affect firms' productivity growth. Empirical studies mainly find that internal knowledge generation through innovation and external knowledge acquisitions are complements, and emphasize the importance of in-house capacity for absorbing external knowledge, consistent with seminal papers by Cohen and Levinthal (1989, 1990) and Rosenberg (1990). There is also a substantial amount of evidence that knowledge transactions and spillovers that influence firm performance can be linked to knowledge sources in the local and regional environment. However, research is less clear about mechanisms for the interplay of knowledge within the company and its geographical environment. The purpose of this paper is to contribute to increased insight into this process, and analyze how it influences firm growth.

The hypotheses we test in this paper are corollaries from the absorptive capacity literature, suggesting that a firm's external knowledge becomes useful when it is combined with internal knowledge and capabilities inside the firm. A large number of studies confirm that there are systematic differences between firms with regard to their level of commitment in innovation efforts, as well as their sustained recurrence of the engagement in renewal activities. Such differences remain persistent over time (Cefis and Orsenigo, 2001; Klette and Kortum, 2004; Peters, 2009; Peters et al., 2013; Duguet and Monjon, 2002). The picture that emerges is that a large share of firms is not engaged in innovation activities, some firms are innovative only occasionally, whereas other firms remain persistently innovative over several years.

The literature provides various explanations for firms' selection into persistent innovation. One strand of the literature stems from evolutionary theory and emphasizes the importance of technological trajectories. Along the technological trajectory, firms learn by innovating and developing organisational competencies (Raymond et al., 2010). Other explanations include the relationships between innovation and market power or financial constraints as selection mechanisms (Brown and Petersen, 2009).

The novelty in our research is that we propose an approach that captures both the intensity of firm knowledge and the availability of external knowledge in the local milieu. To measure the closeness to external knowledge, we rely upon a model for knowledge accessibility suggested by Weibull (1976), which includes a time-sensitive parameter which can be applied for measuring a firm's accessibility to external knowledge. For each firm in a local economy (municipality) we calculate this firm's accessibility to external knowledge: (i) inside the own municipality, (ii) outside the municipality but inside its own functional region, and (iii) outside its functional region. Adding these accessibility measures together for a given local economy provides a measure of the potential opportunities of a firm in the local economy. The paper uses accessibility to knowledge-intensive producer services, KIPS, as a proxy for the mass or amount of influential external knowledge. We assume that this measure captures both intentional knowledge transactions and pure knowledge externalities, especially because KIPS represent activities designed for creation, exchange and transfer of knowledge. In addition, we assume that the capacity of firms to absorb external knowledge is closely correlated with their internal recurring innovation activities. Both KIPS and other producer services represent a growing share of all jobs in the economy, with the largest share in urban agglomerations. This process of growth is stimulated by outsourcing processes in which companies externalize both standard routine services and specialized knowledge services, as well as an overall increased demand for knowledge in manufacturing and service production.

Producer services can affect the performance of other firms in two ways. First, a higher proportion of producer services promote efficient resource allocation, which is then reflected in higher productivity of individual firms and the whole economy. Second, a firm's interaction with knowledge-intensive service suppliers improves the firm's capacity to develop new technology and introduce new products and processes. One reason for this is that since the mission of knowledge intensive service firms is to sell their services and specialized knowledge to more than one client company. With such a sales strategy, novel concepts and solutions are indirectly transmitted from one customer to another.

For each local economy (municipality), our data set contains information on both the number of employed people in knowledge-intensive producer services, the aggregate wage bill of these employees, the number of people commuting to other local economies, and the time distance to other local economies. Thus, for about 5,000 Swedish firms in 290 municipalities and 72 functional regions, based on this information, we can calculate the accessibility to the supply of knowledge intensive producer services for each firm.

For the producer-service provider, the functional region where the firm is located is the home market, inside which the average time interval to customers is 20–30 minutes. Distances to customers in other regions are generally at least two to three times larger. Delineating three groups of regions, we observe that the proportion of KIPS30 is much higher in large urban regions than in medium-sized and small regions, and the accessibility is twice as high for local economies in metropolitan regions as for local economies in the medium-sized regions and small regions.

Internal knowledge factors in this paper are the cumulated result of a firm's recurring engagement in knowledge creation efforts: R&D and innovation activities. In this context we identify three categories of innovation strategies: persistent, recurring R&D engagement, occasional R&D efforts, and no R&D

efforts.

In order to capture each firm's innovation engagement, we use two alternative methods to observe and measure the sustainability over time of a firm's innovation activities. The first approach is to observe and count a firm's national and international patent applications over a sequence of years. The advantage with this measure is that it is observable for all firms along time. The disadvantage is that most innovative activities do not result in any patent or patent application. The second approach is to apply information from the Community Innovation Surveys (CIS), in which data from the EU member states are collected on a regular basis with harmonized information OECD (2015). The attractiveness of the CIS data is that it includes information on the sustainability of the intramural R&D, as well as extramural R&D such as purchase of machinery and equipment and consultancy services. The drawback here is that the reported R&D-engagement only covers a three-year period.

Estimating the economic model with a dynamic GMM estimator, our main results are as follows: (i) The local milieu and the external knowledge potential have no additional productivity growth impact on firms with low internal knowledge; (ii) The growth rate of total productivity is only weakly associated with external knowledge for firms with occasional innovation efforts; (iii) The growth rate of total productivity is strongly associated with external knowledge for firms with persistent innovation efforts; (iv) In all location categories, productivity growth increases with firms' innovation activity The estimation results produce strong evidence of differences in the capacity to benefit from external knowledge among persistent innovators, temporary innovators and non-innovators. The results are consistent regardless of whether innovation efforts are measured in terms of the frequency of patent applications or the rate of R&D investment. Our distinct results support recent studies suggesting that policymakers and managers should not expect that the presence of a knowledge-intensive environment automatically leads to improvements in firm performance. Instead, supportive innovation policies should consider measures that help to maintain and improve the knowledge milieu of places in which many firms follow strategies that give priority to persistent innovation engagement. The remainder of the paper is organized as follows. The next section discusses the relevant literature on internal and external knowledge. Section 3 formulates the hypotheses to be tested and introduce the testing strategy while data is presented in Section 4. Section 5 reports results and interprets the main findings, and Section 6 concludes.

2 A BRIEF BACKGROUND FROM THE LITERATURE

The importance of innovation for sustained growth is well established in the academic literature by Aghion et al. (1998). An early recognition of innovation and technology as engines of growth is the contribution of Schumpeter (1934), arguing that without innovations the market economy would settle in a stationary Walrasian equilibrium. The Schumpeterian view also considers the opportunity of other firms to imitate those firms that have reached a higher productivity level. Adoption processes of this kind could work against heterogeneity. The idea that other firms respond to ideas developed by competitors is a fundamental aspect of the neoclassical theory resembling various versions of Darwinian adjustments (Vega-Redondo (2003)). Empirical research in the Schumpeterian tradition has established several stylized and commonly accepted facts questioning the neoclassical prediction on convergence. These facts include persistent performance heterogeneity and path dependency. Some firms are clearly above average, whereas others are inferior, and that this patterns remains over fairly long time periods. For a review of this literature, see Dosi and Nelson (2010).

Recent studies on firm heterogeneity distinguish between capabilities and technical solutions. The former refer to a firm's capacity to build up renewal capabilities and maintain a resource that includes renewal skills of employees, routines for organization of R&D and efforts to access external knowledge. Firm capabilities also include links to other actors for knowledge accession and collaboration. Technical solutions relate product attributes, production processes and routines, and interaction approaches vis-à-vis input suppliers and customers. For a discussion, see Foss (1996); Antonelli (2006). A major message from this literature is that firms' capabilities differentiate firms. Capabilities take time to develop, require recurrent maintenance, and they are difficult and costly to imitate (Teece (2010)). Moreover, capabilities partly develop as a side effect of a firm's renewal activities, including phenomena like learning by doing (Nelson and Winter (1982); Cohen and Levinthal (1990); Phene and Almeida (2008)). The outcome of the renewal activities is expanded capabilities and enlargement of the firm's technical solutions. Thus, differences in firms' capabilities and internal knowledge resources help explain heterogeneity among firms regarding innovation and imitation/adoption (within firms and across firms) as well as productivity growth.

What about technical solutions? Johansson and Lööf (2014) suggest that firm capabilities determine more than the firm's capacity and its likelihood to succeed in its innovation efforts. They also sharpen adaptability about technical solutions, irrespective of whether they are related to internal or external knowledge about product design, customer preferences, and adjustments of deliveries and the like. The key issue is that the firm has to rely on its internal capabilities to transform technical solutions to productivity growth in an additional creative step.

Concerning knowledge generated outside the firm, this can be accessed by a firm in many different ways. The knowledge may be purchased or transferred according to a license contract, it can move into the firm through new employees who bring with them know-how and knowledge about technical solutions from places where they have worked earlier in their career, and it can spill over from collaborative efforts with other firms and research organizations such as universities.

Besides knowledge flows from the local or regional milieu, the literature also considers knowledge flows through long-distance links of international networks such as imports from input suppliers or export to customers abroad and trans-national links for R&D collaboration with firms abroad. However, recent research in the geography of innovation has established several stylized facts including that knowledge spillovers are typically geographically localized (Feldman (2003)) and fade with distance. This literature is further enriched by studies on technology and market relatedness in the local knowledge milieu (Cassiman and Veugelers (2006)).

Several studies on spillovers suggest a growing productivity potential from local supply of business service due to knowledge spillovers. However, the business service industry consists of a wide variety of firms with different role in the economy. Duranton and Puga (2005) distinguish between three broad categories of business services: standard business (e.g. banking or equipment leasing), sophisticated business services (e.g. research and development) and routinized business services (e.g. call centres). Only the former two are assumed to benefits from geographical proximity and the business potential is related to complementary skills among customers. They can be categorized as knowledge-intensive business services. In this paper we narrow the scope to providers of knowledge-intensive producer services. Producer services generally represent market-supporting services that improve the allocative efficiency of the economy and thus enhance productivity of individual firms. Buyers of these services will benefit because firms within this industry seek to sell their services and specialised knowledge to more than one client company. This implies that they are indirectly transmitting novel concepts and solutions from one customer to another.

There are several papers in different strands of the literature that are close to our study. Lychagin et al. (2016) use U.S. firm level panel data to assess how geographical, technological and product market spillovers contributes to productivity, and find that geography is important for productivity. A number of prior papers have also studied the complementarities between internal knowledge and external knowledge acquisitions. This research supports the assumption that all firms in a local milieu such as a cluster or an agglomeration may not benefit from access to a high concentration of specialized, supplemented or varied knowledge diffused through voluntary (mostly pecuniary) and involuntary mechanisms. Contributors to this literature include Feldman (2003), Conte and Vivarelli (2005), Cassiman and Veugelers (2006), Love and Roper (2009), Antonelli et al. (2013), Lööf and Johansson (2014), and Antonelli and David (2015). For an additional contribution and a survey of the field of research, see Antonelli and Colombelli (2015).

Studying complementary between absorptive capacity and external knowledge, a main message from the literature is that firms near the knowledge frontier will benefit more from external advances in knowledge than other firms. At sufficiently low levels of absorptive capacity, firms might not be able to learn anything from even a rich external knowledge milieu and the “multiplier effect” of potential spillovers is nil.

Recent studies provide evidence for the thesis that the importance of access to external knowledge tends to increase in a knowledge-based innovation-driven economy. In their survey of literature on knowledge spillovers and local innovation, Breschi and Lissoni (2001) argue that when firms are constantly innovating, there is a need to be close to a constellation of allied firms and specialised suppliers to smooth input-output linkages.

Building on the literature reviewed briefly above, the next section formulates the hypotheses we will test empirically using two different sets of Swedish firm level data.

3 EMPIRICAL STRATEGY

The general approach of this paper is the following. First, we group the observed Swedish firms into three categories reflecting their internal knowledge. Second, the external knowledge potential of each firm is also arranged into three categories. These two steps allow us to classify the firms into nine different categories.

In category one, there are firms that do not engage in any innovation activity at all (i.e., patent applications in one of the samples, and R&D in the other sample), and we assume their internal accumulated knowledge to be low. The second consists of firms occasionally conducting innovation activities. Their accumulated knowledge is classified as medium. Firms in final category are persistently engaged in innovation efforts, and consequently they are considered to have a high level of accumulated knowledge. The three categories are labeled I_1, I_2 and I_3, respectively. Correspondingly, the firms are classified into three different groups depending on the availability of knowledge intensive producer services in their vicinity. The three categories are designated K_1, K_2 and K_3.[1]

[1] It should be noted that our knowledge potential indicator also captures the presence of

Based on these groupings of firms, we construct nine combinatorial categories, as illustrated in Table 4. At one extreme, we find firms with low internal knowledge and low external knowledge potential (I_1K_1), and the firm at the other extreme has high internal knowledge intensity and high external knowledge potential (I_3K_3). This formulation enables us to clarify the importance of each IK combination. We may, for example, investigate if a strong knowledge potential can compensate for a low level of internal knowledge. We can also determine if firms with persistent innovation efforts can compensate for a low level of external knowledge potential.

In order to test the relationship between firms' innovation strategies and knowledge spillovers in the local milieu, we formulate four hypotheses. The first hypothesis refers to the combinatorial categories in the I_1 column, comprising firms with a low level of internal knowledge. More formally:

H1: There is no difference in TFP growth across locations for firms that belong to the I_1 group (low degree of internal knowledge), which implies that the local milieu and the external knowledge potential have no additional impact on firms with low internal knowledge. Thus, I_1K_1=I_1K_2=I_1K_3.

Our second hypothesis concerns the I_2 row in Table 4, consisting of firms that make occasional R&D efforts:

H2: There is a difference in the TFP growth for firms that belong to the I_2 classification, such that I_2K_3>I_2K_2>I_2K_1. Thus, the growth rate of firms with occasional occasional innovation efforts increases with access to external knowledge potential.

The third group of firms (I_3) comprises of persistent R&D innovators, and the following hypothesis applies for these firms:

other knowledge sources such as universities, research institutes, and high-technology firms.

H3: There is a difference in the TFP growth for firms that belong to the I_3 classification, such that $I_3K_3 > I_3K_2 > I_3K_1$. Similar to the H2-hypotheses, the a priori assumption is that the growth rate of firms with persistent engagement in innovation is an increasing function of access to external knowledge potential.

Our remaining hypotheses consider only innovative firms. If such firms have the same external potential, we examine if persistent innovators are superior to occasional innovative firms. To accomplish this, we make pairwise comparisons between elements in the I_2 and I_3 rows.

H4: Persistent R&D firms have higher TFP growth than firms with occasional R&D efforts, such that $I_3K_3 > I_3K_2$, $I_2K_3 > I_2K_2$. For all categories of location, there is always a positive improvement in TFP growth from more internal knowledge.

To quantify the relationship between productivity and the input components of interest, we apply an approach aimed at capturing the effect of a particular category of combined knowledge sources on TFP growth, conditioned on the growth in the previous period and the TFP level in the previous period.

Total factor productivity growth is estimated in two steps. Following Levinsohn and Petrin (2003), we first compute TFP as the residual of the Cobb--Douglas production function, where the value added of the firm is the dependent variable and labor inputs (divided into highly educated and unskilled labor), material and physical capital are used as the determinants. In the next step, the growth of TFP is estimated as a function of determinants inside and outside the firm as follows:

$$\begin{aligned}\Delta \log TFP_{i,t} \quad = \quad & \alpha_0 + [I_i \times K_i]\gamma_j + \beta_1 \Delta \log TFP_{i,t-1} + \beta_2 \log TFP_{i,t-1} + \\ & \beta_3 \Delta \log SIZE_{it} + \beta_4 OWN_{it} + \beta_5 SECTOR_{it} + \mu_i + \tau_t + \varepsilon_{it}\end{aligned} \quad (1)$$

where i indexes the firm, t the year, I is a vector of innovation indicators, K

is a vector of external knowledge indicators, $\Delta logTFP$ is the annual growth rate of total factor productivity, TFP is the level of total factor productivity, $\Delta logSIZE$ is employment growth, and $OWNER$ is a set of corporate ownership indicators. Additionally, the TFP growth depends on the sector, and we distinguish between six manufacturing and service sectors. The firm and year-specific effects are denoted by μ and τ, respectively. Finally, ε is the idiosyncratic error term.

The key coefficients of interest are γ_j, which determine the response of productivity growth to nine combinations of internal and external knowledge. It is useful to note that the key variable IK for firm i is almost constant over the period we observe due to the following explanation. First, the I-classification is based on the frequency of innovation efforts during the observed period, which means that it does not vary between years. Second, the K-classification is based on the knowledge intensity of the firm's location, which is close to 100% identical between year t and year $t+1$ according to the transition matrix reported in Table 3.

Based on a procedure proposed by Papke and Wooldridge (2005), we also compute the coefficients and standard errors for long-run effects. The long-run effect is a nonlinear function of the coefficients of the explanatory variables and the lagged dependent variable in Equation (1). This is an alternative method to obtain a standard error for the long-run effect in a dynamic panel data model.

To estimate Equation (1), we use the two-step system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998). This approach combines equations in differences of the variables with equations in levels of the variables. The validity of the instruments in the model is evaluated with the Sargan–Hansen test of overidentifying restrictions whereas the Arellano--Bond AR(2) test is used for identifying possible second-order serial correlation.

An advantage with the system GMM estimator is that it requires fewer assumptions about the underlying data-generating process and uses more complex techniques to isolate useful information (Roodman, 2009). The estimator allows for a dynamic process, with current realizations of the TFP variable influenced by past TFP, and some regressors may be endogenous. Moreover, the system GMM estimator also accounts for individual specific patterns of heteroskedasticity and serial correlation of the idiosyncratic part of the disturbances.

To measure the intensity of external knowledge, we apply a model for knowledge accessibility suggested by Weibull (1976), and developed by Johansson and Klaesson (2011). The model identifies locations i and j, and the time distance (commuting time) between each pair of locations (municipalities). For each location, the associated measure of total knowledge K (total R&D, number of universities, educated workers, etc.) is computed. For any firm in location i, the firm's distance-discounted knowledge potential with regard to K_j is defined as

$$M_{ij} = exp\left\{-\lambda t_{ij}\right\} K_j \tag{2}$$

Where λ is an estimated parameter expressing time sensitivity for making face-to-face contact between individuals (workers) in two locations. If the face-to face contact is within the same location, the firm's distance-discounted knowledge potential is expressed as

$$M_{ii} = exp\left\{-\lambda t_{ii}\right\} K_i \tag{3}$$

The entire external knowledge potential that firms in location i have is calculated as

$$M_i = \sum exp\left\{-\lambda t_{ij}\right\} K_j \tag{4}$$

Note that aggregation is over Sweden's 290 municipalities. This implies that equation (4) can be used for estimating every firm's accessibility to knowledge in their own focal municipality and in all other municipalities.

With this model and data on commuting time between each municipality in Sweden, we calculate each firm's accessibility to external knowledge: (i) inside the own municipality, (ii) outside the municipality but inside the own functional region, and (iii) outside the own functional region. Adding these accessibility measures together for a given local economy provides a measure of the potential opportunities of a firm in the local economy.

4 DATA AND VARIABLES

In our empirical investigation, we use manufacturing and service firm-level data provided by Statistics Sweden. The database contains accounting information on all firms in Sweden, information on the educational background and wages of their employees and location of the firms.

In order to quantify external knowledge potential at the firm level, we first identify 35 Swedish knowledge-intensive producer service (KIPS) industries[2] in which the share of employees with university degrees is over 30 percent. We then use firms' accessibility to producer services as a proxy for the availability of external knowledge. The measure is constructed from the aggregate earnings, or wage bill, for each of the producer service industries in Sweden's 290 municipalities. The larger are aggregate earnings, the larger amount of external knowledge in a particular municipality.

One-third of each of the approximately 400,000 Swedish firms are located in 25 municipalities, areas with high access to local knowledge according to our definition. An additional third of these firms are found in 78 municipalities classified as areas with medium access to potential external knowledge, and the

[2]A list of these industries is given in Appendix Table A.1.

remaining firms are located in 187 municipalities with low access to potential external knowledge.

As a second step, we form two panels of firms. In the first panel, the patent panel, we have matched patent data to the entire population of firms in the Swedish business sector. In the second panel, we match R&D data from the Community Innovation Survey (CIS) to a selected group of firms. Both panels are restricted to firms with at least 10 employees.

For the patent panel, we use information from the European Patent Office's worldwide patent statistical database (PATSTAT) complemented with data from the Swedish Patent Office. The panel consists of 35,108 unique firms, approximately 1,600 of which applied for at least one patent between 1997 and 2008.

The CIS panel considers only those firms that participated in at least two of three consecutive Community Innovation Surveys (CIS) for 2004, 2006 and 2008. The matched data contain 2,539 unique firms. Both panels are unbalanced, and the second is observed only for the 2000--2008 period. More than 99 per cent of firms remain in one place over any two consecutive years, so we only use the data on firms that did not change their location in the period of study.[3]

Using patent applications, we classify firms as persistent innovators, occasional innovators and non-innovators based on observations over the entire 12-year period in the patent panel.

An obvious limitation of employing CIS data in a panel setting is that almost all the information pertains only to particular years. One of the few exceptions is the frequency of R&D engagement, where the perspective comprises the most recent three-year period. However, such a period is also too short for the purposes of our research. To extend this information, we construct a data set

[3]We also estimated using the full sample. The results are similar and available upon request.

from three different waves of the CIS survey. In the resulting CIS panel, 40% of firms are observed in all three surveys, and 60% are observed in two surveys. With overlapping data from the three surveys, we can observe the selected firms' innovation strategies over a minimum of 5--7 years.[4]

Columns 1, 3 and 5 in Table 1 present summary statistics for the patent panel, with firms separated into three groups reflecting their long-term innovation strategies. If a firm applied for at least one patent annually during six or more years,[5] we categorize the firm as a persistent innovator. If it applied for at least one patent annually during 1-5 years, we consider it an occasional innovator. Firms with no patent applications are classified as non-innovators. Table 1, columns 2, 4 and 6 reports the summary statistics for firms observed in the CIS surveys. We classify a firm as a persistent innovator period if it is reported to be a persistent R&D investor in at least two out of the three CIS surveys. Moreover, the firm is classified as non-innovative if it is never reported to be R&D-active. All other firms are considered to be occasional innovators.

In the patent panel, which includes all the approximately 35,000 relevant firms in Sweden, 95% are classified as non-innovative, 4% are classified as occasional innovators and 1% are classified as persistent innovators. In the CIS panel, 45% of firms are defined as non-innovative, 38% are occasional innovators and 17% are persistent innovators.

[4] The observations for the years 1997--1999 are utilized to create lags of the dependent variables. It should be noted that the panel is unbalanced in the sense that we include two voluntary surveys and one compulsory survey, which can cause some selection bias. For instance, the fraction of innovators is 31% in the CIS 2008 data and 54%, on average, in the CIS 2004 and 2006 data.

[5] For a robustness check, a threshold of 8 years instead of 6 years is also considered. The results are similar.

Consistent with our assumptions based on the literature review in Section 2, the mean values of most variables differ for persistently innovative firms compared with firms with no innovation activity or only temporary engagement. Persistently innovative firms are larger than occasionally innovative firms, they have more physical capital, and higher intensities of human capital as well. They are also more likely to belong to multinational groups.

The summary statistics shows only minor differences in TFP growth between firm categories in both panels. As could be expected, persistent innovators are more oriented toward high technology and medium-high technology than other firms.

Table 2 displays the distributions of the 66,719 observed patent applications across markets, firm sizes, corporate ownership groups and sectors. The vast majority of patent applications are related to firms with more than 100 employees, a large fraction of which are multinational enterprises (MNEs). Domestic MNEs account for nearly 60 per cent of the applications, and foreign-owned MNEs account for 35 per cent. The most patent-intensive sectors are high and medium-high technology firms in the manufacturing sector. Knowledge-intensive services are more likely to apply for patents than are low or medium-low technology manufacturing firms.

5 ESTIMATION RESULTS

Table 5 presents estimates of Equation (1) using a two-step dynamic GMM estimator with total factor productivity growth (TFP) as the dependent variable. Table A.2 in the appendix reports the pooled OLS estimates. Columns 1 and 2 report short- and long-run estimates for the sample that include the entire population of firms with an average of 10 or more employees over the period 1997--2008, whereas Columns 3 and 4 report the corresponding estimates for the CIS population, which is restricted to a stratified sample with a firm size of 10 or more employees in the year of the surveys.

The key results are presented in the upper part of the table which is organized in three different panels. In the first panel, rows 1–3 show results for non-innovative firms. In the second panel, rows 4–6 show coefficients for temporary innovators. The third panel presents TFP growth with respect to persistently innovative firms in different locations in rows 7–9.

Basic results

Using I_1K_1 in Table 5 as the reference group, the estimates in the first panel are small in absolute value and statistically significant only in the patent panel for the non-innovative firms located in regions with a medium intensity of external knowledge. However, the sign is negative. Our first conclusion, which applies for both the patent- and CIS-panels is that there are almost no growth effects from the local milieu for non-innovators.

The section with occasional innovators reports that the estimates are positive and significantly different from the base group in all three locations for the patent panel. Moreover the growth rate is markedly higher among temporary innovators in milieus where firms have high access to knowledge sources, compared to firms in milieus with medium or low access to external knowledge (0.047 versus 0.015 and 0.017, respectively). The CIS panel shows positive signs on the coefficients, but the estimated effects are insignificant or only weakly significant.

The final set of results presented in Table 5 concerns TFP growth among persistent innovators. Rows 7--9 provide a consistent picture for both samples. First, persistent innovators always have higher TFP growth than other firms, regardless of location. Second, the growth rate for persistent innovators increases with access to external knowledge. The size of the estimates is largest for persistent innovative firms located in areas with high access to external knowledge. The magnitude of the estimate is 0.14 in the patent sample and 0.11 in the CIS sample.

Table 5 also presents the long-run estimates for the two samples, given in Columns 2 and 4, and these results are fully consistent with the short-run estimates in Columns 1 and 3. The only difference is that the standard errors deviate slightly in some cases.

Examining the covariates displayed in Table 5, we find negative signs for both TFP growth and TFP level in the previous year. While the latter indicates a tendency to convergence in line with predictions from growth theory, the former deserves some comments. Why is growth in a given year a negative function of last year's growth rate in our data? There might be a possibility that firms in general simply follow a quiet-life behaviour pattern. Hence, the improvement in the performance yesterday reduces the incentives for firms to invest their efforts in better performance (growth) today. Instead they decide to enjoy the fruits of their earlier activities. For a discussion on similar findings, see Hashi and Stojčić (2013).

Turning to other controls, the table report positive coefficient estimates for firms, but significant different from zero only in the CIS-sample. As could be expected, multinational firms have a higher growth rate than other firms, *ceteris paribus*.

The test statistics are reported in the lower part of Table 5. We use lag limits t-4 instruments for the regression in differences in both panels and lagged differences dated t-1 for the regression in levels in the patent panel and t-3 in the CIS panel. This results in 112 instruments in the patent panel regression and 104 instruments in the CIS panel regressions, which are both within a reasonable range. The AR(2) test does not detect second-order autocorrelation in the firstdifferenced residuals in both regressions. Otherwise, the GMM estimator could be inconsistent. The Hansen J-test of overidentifying restrictions confirms that the instruments are valid, and the difference-in-Hansen test confirms that the additional instruments required for systems estimation are valid for the two regressions.

Overall, the results in Table 5 indicate a strong, positive relationship between internal and external knowledge for innovators. This conclusion applies regardless of the proxy for innovative activity.

To evaluate the quantitative importance of the IK coefficients in detail, we conduct a Wald test on the equality of means in Table 6. The first prediction from our model is that the local milieu and the external knowledge potential have no additional impact on firms with low internal knowledge. The H1 section of the table indicates that non-innovators in places with medium access to knowledge outside the firm have only somewhat lower growth rates than the reference group (non-innovators in locations with low access to external knowledge) in the patent panel. No significant difference is found in the CIS panel. We therefore confirm Hypothesis 1.

Our second prediction (H2), that the growth rate of an innovative firm increases with access to external knowledge, even though the renewal engagement is temporary, is partly confirmed when the patent panel is considered. Occasional innovators in high-access areas have higher productivity growth than occasional innovators located in other places. However, no significant difference exists in the growth means between firms that are occasionally engaged in places with low and medium access to external knowledge. Concerning the CIS-panel, the t-test are not significant or only weakly significant.

The third hypothesis predicts that the growth rate of persistent innovative firm increases with access to external knowledge. The results for the patent panel in the H3 section indicate that persistent innovators in the most knowledge intensive locations grow significantly faster than corresponding firms in other locations. Moreover, persistent innovators in places with medium knowledge intensity have higher growth rates than persistent innovators in locations characterized by low knowledge intensity.

The coefficient estimates for the CIS-panel in Table 5 suggests persistent innovative firm increases with access to external knowledge, but the t-tests only confirm the hypothesis when I_3K_3 is compared with I_3K_1. However, taking both panels into account, the overall conclusion from the H3 section is that we cannot reject the hypothesis that growth rates will increase with access to knowledge the local milieu for persistent innovative companies.

Our final prediction (H4) considers only innovators and hypotheses that a positive return to improvement of internal knowledge always applies for all categories of location for innovative firms. The prediction is strongly confirmed in both of our panels[6] The main difference is in the sizes of the estimates, which are lower when using the OLS estimator. The pooled OLS estimator suffers from omitted variable bias and potential endogeneity.

What then are the common observations in the three tables? Table 5 and Table A2 in the appendix reveal four regularities that persist in alternative specifications and estimators. First, the differences in the coefficient estimates among non-innovators in different locations are negligible. Second, our evidence that occasionally innovative companies grow faster in a knowledge-intensive envi-

[6] A fixed-effect model is used to estimate the lag of the dependent variable for all regressions. The results indicate that the coefficients on lagged dependent variables using the GMM estimator are higher than the coefficients obtained for the fixed effect model and lower than the OLS estimates, as expected given the opposing biases of pooled OLS and fixed effects models. The results are available upon request.

ronment is weak. Third, the growth rates for persistently innovative firms in locations with high access to external knowledge are always higher than those of firms in other locations, regardless of innovation strategy. Finally, for persistent innovators, the growth rates are always increasing with the amount of external knowledge.

6 CONCLUSIONS

This paper suggests an approach for quantifying the extent of potential external knowledge across regions and linking this potential to local firms' innovation strategies. We model knowledge inputs in a production function by using a discrete composite variable with different combinations of the intensity of knowledge from within and from outside the firm. With our approach, the results indicate that the benefits of knowledge-intensive local milieus are not uniformly distributed across different types of firms. We only find strong effects on TFP growth for persistent innovators. We do not detect any substantial effect for occasional innovators, nor any effects for the non-innovators, which constitute the vast majority of all firms.

Thus, while the policy debate tends to assume that firms located in knowledge-rich milieus such as urban agglomerations and specialized spatial clusters will profit from proximity to diversified knowledge and supply of knowledge-intensive producer services, in technology, law, finance, management, marketing and other support functions, the study contributes to a more nuanced discussion.

Our distinct results support recent studies suggesting that policymakers and managers should not expect that the presence of a knowledge-intensive environment automatically leads to improvements in firm performance. Instead, supportive innovation policies should consider measures that help to maintain and improve the knowledge milieu of places in which many firms follow strategies that give priority to persistent innovation engagement. The result from our study also raises the complex question: which policies can facilitate the transition of a firm from a state of being an occasional innovator to being persistently engaged in innovation efforts? Occasional efforts include disruptions that can cause the erosion and obsolescence of acquired skills, routines and technology.

The policy nexus of our study is two-pronged. A firm's knowledge management comprises (i) systematic accumulation of internal knowledge combined with the development of absorption and accession capacity, and (ii) location in a knowledge-intensive environment. The basic policy message is that these two components are not substitutes, but rather complements.

There are several limitations of this study that can become questions for future research. First, the issue of knowledge flows across firms that are not related to links within the nearby milieu of the firms is not explicitly addressed in this paper, except for the effect associated with multinational company groups. Recently Cantwell and Piscitello (2015) have used openness of the regional industry and the regional economy to capture global knowledge diffusion, while other papers apply methods such as trade statistics, patent citations and strategic alliances. A second issue that deserves a more subtle analysis than is provided in the present paper is the nature of internal mechanisms for creating and maintaining conduits to the external environment that facilitate knowledge flows to the firm.

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7 Tables

Table 1: Descriptive statistics for 1997–2008. Innovation strategy based on patent applications and the CIS panel (mean and standard errors reported)

	(1) Non R&I		(2) Occasional R&I		(3) Persistent R&I	
	Patent	CIS panel	Patent	CIS panel	Patent	CIS panel
TFP growth ^{a,c}	0.05	0.03	0.04	0.03	0.04	0.03
	(0.46)	(0.37)	(0.48)	(0.37)	(0.49)	(0.41)
Human capital ^{b}	0.11	0.08	0.15	0.12	0.22	0.22
	(0.17)	(0.14)	(0.19)	(0.18)	(0.21)	(0.22)
Firm size ^{a}	3.04	3.28	3.78	3.75	4.83	4.79
	(0.97)	(1.17)	(1.28)	(1.38)	(1.61)	(1.70)
Firm size growth	0.05	0.04	0.04	0.05	0.03	0.03
	(0.38)	(0.27)	(0.30)	(0.28)	(0.26)	(0.24)
Physical capital ^{a,c}	13.46	14.05	14.90	14.83	16.36	16.33
	(2.85)	(2.98)	(2.58)	(2.66)	(2.72)	(2.91)
Domestic Non Affiliated Firms	0.45	0.38	0.20	0.26	0.08	0.12
Domestic Affiliated Firms	0.34	0.33	0.23	0.30	0.10	0.17
Domestic Multinational Firms	0.11	0.13	0.36	0.20	0.47	0.39
Foreign Multinational Firms	0.10	0.16	0.21	0.24	0.35	0.32
High tech manufact^{b}	0.01	0.04	0.07	0.06	0.17	0.18
Medium-High tech manu^{b}	0.05	0.12	0.28	0.19	0.36	0.28
Medium-Low tech manu^{b}	0.09	0.15	0.21	0.18	0.17	0.15
Low tech manu^{b}	0.10	0.24	0.12	0.27	0.06	0.16
Knowledge-intense serv^{b}	0.27	0.17	0.14	0.16	0.12	0.18
Other serv^{b}	0.46	0.25	0.18	0.12	0.10	0.04
Mining ^{b}	0.02	0.03	0.00	0.02	0.02	0.01
Observations total	274,396	9,633	12,053	7,810	3,713	3,616
Unique firms	33,497	1,165	1,255	936	356	438
Observations, fraction	0.95	0.46	0.04	0.37	0.01	0.17

Note: a)Log, b)Fraction, c)Real prices

Table 2: Distribution of patent applications during the 1997-2008 period by firms in Sweden across regions and groups

	Number of Applications	Occasional R&I, %	Persistent R&I, %
Knowledge access: Low	6,947	0,25	0,75
Knowledge access: Medium	31,089	0,05	0,95
Knowledge access: High	28,590	0,06	0,94
10-25 employees	3,308	0,47	0,53
26-99 employees	5,860	0,32	0,68
100+ employees	57,458	0,03	0,97
Domestic Non Affiliated Firms	2,427	0,39	0,61
Domestic Affiliated Firms	2,301	0,37	0,63
Domestic Multinational Firms	38,364	0,05	0,95
Foreign Multinational Firms	23,534	0,05	0,95
High tech manufacturing	31,572	0,02	0,98
Medium-High tech manufacturing	16,361	0,10	0,90
Medium-Low tech manufacturing	5,510	0,15	0,85
Low tech manufacturing	3,549	0,14	0,86
Knowledge-intense services	7,202	0,12	0,88
Other services	2,339	0,35	0,65
Mining	93	0,22	0,78

Table 3: Transition Matrix

	Access to external knowledge	No R&I,%	Occasional R&I,%	Persistent R&I,%
Patent panel	Low	99.3	99.6	99.1
	Medium	99.1	99.1	99.3
	High	99.4	98.9	99.0
CIS panel	Low	99.5	99.5	99.6
	Medium	99.5	99.1	99.5
	High	99.4	98.9	99.5

Note: The matrix shows that all firms in all three categories of geographical areas tend to remain in the same place across time.

Table 4: Combinatorial categories of internal (I) and external (K) knowledge

	K_1	K_2	K_3
I_1	I_1K_1	I_1K_2	I_1K_3
I_2	I_2K_1	I_2K_2	I_2K_3
I_3	I_3K_1	I_3K_2	I_3K_3

Table 5: Two-step system GMM estimates of TFP growth

Innovation variable	Patent Panel		CIS Panel	
	Short-run	Long-run	Short-run	Long-run
I_1 K_1[a]	0.000	0.000	0.000	0.000
I_1 K_2	-0.005*	-0.004**	-0.012	-0.010
	(0.00)	(0.00)	(0.01)	(0.01)
I_1 K_3	0.002	0.002	0.000	0.000
	(0.00)	(0.00)	(0.01)	(0.01)
I_2 K_1	0.017***	0.015***	0.007	0.006
	(0.01)	(0.01)	(0.01)	(0.01)
I_2 K_2	0.015**	0.013**	-0.002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)
I_2 K_3	0.047***	0.039***	0.021*	0.018*
	(0.01)	(0.01)	(0.01)	(0.01)
I_3 K_1	0.045***	0.038***	0.062**	0.053**
	(0.03)	(0.01)	(0.03)	(0.02)
I_3 K_2	0.085***	0.072***	0.094***	0.081***
	(0.03)	(0.02)	(0.03)	(0.03)
I_3 K_3	0.140***	0.119***	0.112***	0.097***
	(0.05)	(0.03)	(0.03)	(0.03)
Log Firm size, growth	0.047	0.079	0.207*	0.227**
	(0.05)	(0.05)	(0.12)	(0.11)
Log TFP growth$_{t-1}$	-0.181**		-0.154	
	(0.06)		(0.10)	
Log TFP$_{t-1}$	-0.144***		-0.289***	
	(0.04)		(0.09)	
Domestic Affiliated[b]	0.020**	0.017**	0.024	0.021
	(0.01)	(0.01)	(0.02)	(0.01)
Domestic multinational[b]	0.053***	0.045***	0.119***	0.103***
	(0.02)	(0.02)	(0.05)	(0.04)
Foreign multinational[b]	0.062***	0.053***	0.126***	0.109***
	(0.02)	(0.02)	(0.05)	(0.04)
Observations	183,490		18,769	
Unique firms	29,154		2,462	
Lag limits	(4 1)		(4 3)	
Instruments	112		104	
AR(2)	0.872		0.786	
Hansen Overid.	0.278		0.137	
Diff-in-Hansen test level eq.	0.146		0.283	
Diff-in-Hansen test lag dep.	0.211		0.797	

Note: * significant at 10%; ** significant at 5%; *** significant at 1%

Robust (GMM) standard error in parentheses. Year and sector dummies included

(a) Reference group (b) Reference group is domestic non-affiliated firms

[I_1 K_1:Non R&I and Low access]; [I_1 K_2:Non R&I and Medium access]; [I_1 K_3:Non R&I and High access] [I_2 K_1:Occational R&I and Low access]; [I_2 K_2:Occational R&I and Medium access]; [I_2 K_3:Occational R&I and High access] [I_3 K_1:Persistent R&I and Low access]; [I_3 K_2:Persistent R&I and Medium access]; [I_3 K_3:Persistent R&I and High access]

Table 6: t-tests for the equality of means reported as p-values

	Hypotheses	Patent panel	CIS panel
		t-test	t-test
I_1 K_3=I_1 K_2	H1	0.00***	0.23
I_1 K_3=I_1 K_1	H1	0.05**	0.21
I_2 K_3=I_2 K_2	H2	0.01***	0.09*
I_2 K_3=I_2 K_1	H2	0.01***	0.21
I_2 K_2=I_2 K_1	H2	0.79	0.41
I_3 K_3=I_3 K_2	H3	0.03**	0.38
I_3 K_3=I_3 K_1	H3	0.00***	0.02**
I_3 K_2=I_3 K_1	H3	0.01***	0.12
I_3 K_3=I_2 K_3	H4	0.00***	0.00***
I_3 K_2=I_2 K_2	H4	0.02**	0.00***
I_3 K_1=I_2 K_1	H4	0.04**	0.02**

Note: The table report t-test for hypotheses H1-H4.

P-values and degrees of significance are reported.

* significant at 10%; ** significant at 5%; *** significant at 1%

[I_1 K_1:Non R&I and Low access]; [I_1 K_2:Non R&I and Medium access]; [I_1 K_3:Non R&I and High access] [I_2 K_1:Occational R&I and Low access]; [I_2 K_2:Occational R&I and Medium access]; [I_2 K_3:Occational R&I and High access] [I_3 K_1:Persistent R&I and Low access]; [I_3 K_2:Persistent R&I and Medium access]; [I_3 K_3:Persistent R&I and High access]

8 Appendix

Table A.1: Knowledge intensive producer services with more than 30% knowledge intensity in 2007

SIC 2002	Industry	Knowledge intensity,%	Fraction KIPS30
7220	Software consultancy and supply	46,1	18,45
74202	Construction and other engineering activities	38,4	16,84
65120	Monetary intermediation	32,5	12,28
74140	Business and management activities	45,2	11,16
74120	Accounting, book-keeping & auditing activities	41,2	7,71
72210	Publishing of software	50,3	5,13
74501	Labor recruitment activities	35,9	3,98
73102	R&D on engineering and technology	68,5	3,15
74111	Legal advisory	70,9	2,45
74850	Secretarial and translation activities	32,9	2,00
65220	Credit granting	31,7	1,90
61102	Sea and costal water transport	42,8	1,90
74201	Architectural activities	67,1	1,84
73103	R&D medical and pharmaceutical science	69,7	1,50
73101	R&D on natural science	74,3	0,97
74104	R&D on agricultural science	67,1	0,92
74130	Market research and public opinion polling	36,1	0,87
74872	Design activities	32,4	0,86
67120	Security broking and fund management	52,7	0,84
66012	Life insurance	33,8	0,79
67202	Activities auxiliary to insurance and pension funding	31,6	0,74
72400	Data base activities	31,7	0,70
65232	Unit trust activities	36,5	0,58
65231	Investment trust activities	49,7	0,53
74112	Advisory activities concerning patents and copyrights	50,2	0,45
73201	R&D on social science	79,9	0,44
73202	R&D on humanities	80,1	0,27
74150	Management activities of holding companies	34,9	0,22
67110	Administration of financial markets	48,6	0,13
65110	Central banking	54,0	0,11
66020	Pension funding	40,6	0,09
73105	Interdisciplinary R&D on natural science & Eng.	69,9	0,08
65210	Financial leasing	31,2	0,06
73201	Interdisciplinary R&D on humanities & social science	77,8	0,04
70110	Development of selling of real estate	40,5	0,02

Table A.2: Regression results for pooled OLS estimates of TFP growth

Innovation variable	TPF growth	TPF growth
	PATENT	CIS
$IK_{11}{}^{a}$	0.000	0.000
IK_{12}	-0.004**	-0.006
	(0.002)	(0.007)
IK_{13}	0.004*	0.003
	(0.002)	(0.008)
IK_{21}	0.014***	-0.003
	(0.006)	(0.007)
IK_{22}	0.012	0.001
	(0.008)	(0.008)
IK_{23}	0.044***	0.014
	(0.009)	(0.009)
IK_{31}	0.035***	0.014
	(0.010)	(0.011)
IK_{32}	0.073***	0.038***
	(0.012)	(0.012)
IK_{33}	0.144***	0.063***
	(0.020)	(0.013)
Log Firm size, growth	0.315***	0.215***
	(0.008)	(0.017)
Log TFP growth$_{t-1}$	-0.329***	-0.327***
	(0.006)	(0.018)
Log TFP$_{t-1}$	-0.123***	-0.126***
	(0.003)	(0.007)
Domestic Affiliated^{b}	0.015***	-0.009
	(0.002)	(0.005)
Domestic multinational^{b}	0.044***	0.030***
	(0.003)	(0.008)
Foreign owned multinational^{b}	0.054***	0.032***
	(0.004)	(0.008)
Observations	183,490	18,769

Note: * significant at 10%; ** significant at 5%; *** significant at 1%

Robust standard error in parentheses, Year and sector dummies included.

(a) Reference group (b) Reference group is domestic non-affiliated firms

[I_1 K_1:Non R&I and Low access]; [I_1 K_2:Non R&I and Medium access]; [I_1 K_3:Non R&I and High access] [I_2 K_1:Occational R&I and Low access]; [I_2 K_2:Occational R&I and Medium access]; [I_2 K_3:Occational R&I and High access] [I_3 K_1:Persistent R&I and Low access]; [I_3 K_2:Persistent R&I and Medium access]; [I_3 K_3:Persistent R&I and High access]