Innovation, Spillovers and Productivity Growth: A Dynamic Panel Data Approach

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Abstract

This paper examines variation in productivity growth within a given location and between different locations. Implementing a dynamic panel data approach on Swedish micro data, we test the separate and complementary effect of internal innovation efforts and spillovers from the local milieu. Measuring the potential knowledge spillover by access to knowledge intensive services, 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 R&D investments.

Keywords: Innovation, spillovers, TFP-growth, panel data
JEL-Codes: C23, O31, O32

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1 INTRODUCTION

Given the attention that firms' engagement in research and innovation and their geographical location have attracted in the last decades, as well as the increased access to both detailed firm level data and regional data, surprisingly few studies have been able to assess the separate and complementary effect of these two production factors within the same framework.

In order to fill this gap, our paper provides empirical evidence on the impact of internal knowledge generation and knowledge spillovers from neighboring firms on firms' productivity growth. We proxy the first factor by the frequency of innovation efforts, and the second by the intensity of local knowledge sources.

In a dynamic framework, we then consider various innovation strategies in a particular location, and a particular innovation strategy in different locations. Using this methodology, we are able to test if firms with persistent frequency of innovation activities can overcome a low level of external knowledge potential, and whether a high external knowledge potential can compensate for a low level of internal knowledge.

Our empirical analysis applies to Swedish firm-level observations on manufacturing and service firms and we study two different time periods. In cases where patent applications are used to capture the innovation strategy (or internal knowledge generation) of the firm, the period studied extends from 1997 to 2008. In the second case, where R&D engagement information is used, the study employs survey data from three consecutive Swedish Community Innovation Surveys (CIS), covering the period 2002-2008. We use access to knowledge-intensive producer services as indicator for the mass or amount of influential external knowledge in the local milieu. In the empirical analysis, the paper identifies 35 Swedish producer-service industries at the 5-digit level in which more than 30 per cent of employees have a university degree. These services include ICT services, engineering R&D and engineering services, financial services, and the brokerage and recruitment of manpower.

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 R&D investments. We do not find any differences in growth among non-innovative firms across locations, while the growth rate increases with the access to external knowledge for innovative firms.

The remainder of the paper is organized as follows: the next section discusses the relevant literature on internal and external knowledge and clarifies our theoretical assumptions. It also presents the hypotheses to be tested. Section 3 describes the data, and Section 4 introduces the testing strategy and the associated model specifications. Section 5 discusses and interprets the main findings, and Section 6 concludes.

2 LITERATURE REVIEW

The objective of our research is to clarify the idea of a symbiotic relationship between research and innovation (R&I) and spillovers by distinguishing between different levels and combinations of internal and external knowledge. In this section we will briefly review literature on heterogeneity and persistence concerning firms' productivity and innovation activities. We then consider literature on spatial proximity to knowledge with business potential. Finally, we discuss the literature on absorptive capacity which suggests complementary between a firms own R&D and external knowledge before introducing our empirical model.

Innovation, persistency and performance

A growing body of empirical literature documents the existence of performance heterogeneity across firms and establishments. This observation remains valid for several performance measures, including profitability, productivity and growth (Bartelsman and Doms, 2000). To a large extent, the heterogeneity also tends to persist over long periods (Mueller, 1986; Cubbin and Geroski, 1987; Geroski and Jacquemin, 1988; Geroski, 1998; Gschwandtner, 2005; Syverson, 2004, 2011; Dosi, 2007). Surveying the micro literature, Dosi and Nelson (2010) find that the heterogeneous productivity pattern can be explained by different abilities to innovate and/or adopt innovations developed elsewhere.

Previous studies have documented that, in most fields of innovation and technology, progress is cumulative in the sense that today's efforts build on preceding efforts. Prior experience from related projects can create internal capabilities within organisations, and learning economies and these categories of internal spillovers tend to reduce the costs of new innovation (Nelson and Winter, 1982; Attewell, 1992; Cohen and Levinthal, 1990; Åstebro, 2002; Phene and Almeida, 2008; Teece, 2010). Thus, the continuity of innovation efforts ensures the accumulation of internal knowledge, whereas disruption can cause the erosion and obsolescence of acquired skills, routines and technology.

The overall picture that emerges from recent empirical studies, however, indicates that many firms are not at all engaged in innovation and R&D activities: some are innovation-active only occasionally, and others remain persistently innovation-active over periods of years (Cefis and Orsenigo, 2001; Klette and Kortum, 2004; Peters, 2009; Peters et al., 2013; Duguet and Monjon, 2002).

The literature provides various explanations for firms' selection into persistence of innovation or not. One element of the literature stems from evolutionary theory and emphasises 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).

Knowledge external to the firm

Firms do not learn solely from internal spillovers across projects and time. A common element of many theoretical propositions in the productivity literature and related economic models (Marshall, 1890; Arrow, 1962; Jacobs, 1969; Porter, 1990; Romer, 1986) is the hypothesis that a firm or an industry benefits from spatial proximity to knowledge. The presence of external knowledge flows should reveal itself in social returns to innovation efforts in addition to private returns[1]. Numerous studies have clarified that the social rate of return is larger in agglomeration areas, and that knowledge flows decline in volume and intensity as the distance between origin and destination increases[2] [3].

A local environment with a wide spectrum of knowledge resources and a wide range of qualifications and competence profiles regarding the labour supply pro-

[1] In a recent analysis based on technology flows across industries, Wolff (2012) finds that the direct rate of return to R&D in the US between 1958 and 2007 was 22%, whereas the indirect rate of return to R&D was 37%.

[2] Friction costs vary for both non-market spillover and commercial transfers because of communication distances. Distance frictions increase when knowledge is complex (Beckmann, 2000) and when it is tacit (Polany, 1966). Knowledge also has a tendency to be spatially sticky (von Hippel, 1994).

[3] Consistent with predictions from gravity models, Glaeser and Gottlieb (2009) estimate that the elasticity of income with respect to city size in the U.S. is within the range of 0.04-0.08 for different model specifications. The size of the estimates is comparable with estimates by Ciccone and Hall (1996), who find that a doubling of employment density in a county results in a 6% increase in average labour productivity. Using patent data, several studies indicate that the number of cross-citations significantly decreases as distance increases (Maurseth and Verspagen 2002, Verspagen and Schoenmakers 2000). Testing hypotheses on variety, Frenken, Van Oort, and Verburg (2007) report that Dutch regions with a high degree of related variety had the highest rates of growth in employment. Focusing explicitly on innovations, Brouwer et al. (1999) demonstrate that firms located in agglomerated Dutch regions tend to produce larger numbers of new products than firms located in more rural regions. Similar result is reported by Doloreux and Shearmur (2012).

vides rich opportunities for knowledge exchange and creative interaction between firms and individuals. As a rule, these features apply to large urban regions in which the knowledge potential is higher than elsewhere. The importance of proximity between suppliers and buyers of knowledge-intensive producer services can be linked to the theory of agglomeration economies in large urban regions, according to which large regions offer companies more positive externalities than small regions. Fujita and Thisse (2002) describe this phenomenon as "communication externalities". They measure the extent of the agglomeration advantage of a single firm by the company's accessibility to other companies.

Recent studies provide evidence for the thesis that 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 system, Breschi and Lissoni (2001) argue that when firms are constantly innovating there is the need to be close to a constellation of allied firms and specialised suppliers to smooth input-output linkages. Consistent with this reasoning, several works suggest that a focus only on internal knowledge and the development of internal capabilities and routines is no longer sufficient for coping with challenges such as shorter product life cycles, greater technological complexity, more specialised knowledge and increasing cost. Therefore, firms need to tap into external knowledge sources. See, for instance, Czarnitzki and Hottenrott (2009), who find that highly skilled labour and the proximity to suppliers matter for firms' innovation performance in Belgium. Similar results are provided by Saito and Gopinath (2011).

Recent empirical evidence suggests a growing business potential from local supply of business service due to knowledge spillovers. A key explanation is that their service is shared by different firms and in different sectors. This development is especially prevalent in urban environments. For a discussion, see

Duranton and Puga (2005)

Absorptive capacity

A growing number of empirical studies on the complementarities between internal knowledge and external knowledge acquisitions questions the assumption that all firms in a milieu such as a cluster or an agglomeration are able to assimilate knowledge from its environment. mechanisms. Typically, the empirical studies find that internal knowledge generation through in-house R&D efforts and external knowledge acquisitions are complements and emphasise the importance of in-house capacity for absorbing external knowledge, consistent with seminal papers by Cohen and Levinthal (1989). The complementary between absorptive capacity and external knowledge suggests that firms near the knowledge frontier will benefit more from external advance 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 mileu and the ´multiplier effect´ of potentail spillovers is zero.

Based on the findings from the literature discussed above, our a priori assumption in this paper is that firms with much internal knowledge, as measured by persistent innovation activities, are better placed than other firms to assimilate external local knowledge. We also assume that that the multiplier effect of spillovers increases with the availability of external knowledge.

3 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 the location of the firms.

The analysis applies information about the entire population of firms in the Swedish business sector with at least one employee, and the entire population of employees within these firms in the following ways. First, we calculate the aggregate earnings (wage sum) in each of Sweden's 290 municipalities for all 35 industries that are classified as knowledge-intensive producer services (a list of these industries is provided in the Appendix Table A.1). This is our proxy for external knowledge potential. Second, we assign a value of access to potential knowledge to each firm in the Swedish business sector based on the particular municipality in which they are located. Third, we separate the firm's into three evenly distributed groups based on their potential access to external knowledge.

One-third of each of the approximately 400,000 existing Swedish firms are located in places defined as high accessibility areas and they are concentrated in 25 municipalities. An additional third of these firms are found in 78 municipalities classified as areas with medium access to potential external knowledge, and the remaining firms are located in 187 municipalities with low access to potential external knowledge. With this approach, we capture both the individual firm's proximity to nearby knowledge and the firm's proximity to other firms with similar access to knowledge-intensive producers.

As a second step, we form two panels of firms. In the first panel (i.e., the patent panel), we have matched patent data to the entire population of firms in the Swedish business sector, whereas we match R&D data from the Community Innovation Survey (CIS) in the second panel (i.e., CIS panel). The preferred patent panel is restricted to firms with at least 10 employees on average over the 1997-2008 period. The restriction is motivated by our ambition to compare the empirical analysis using this panel with the same empirical approach applied to CIS data. In Sweden, 10 employees is the lower size limit for participation in the CIS studies.

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, but we only use the data on firms that did not change their location in the period of study.[4]

Using national and international 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 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 5-7 year period.[5]

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

[5] However, the observations for the years 1997-1999 are utilized to obtain 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.

Table 1 presents summary statistics for the 1997-2008 period, with firms separated into three groups reflecting their long-term innovation strategies. Consider first the patent panel in Columns 1, 3 and 5. If a firm applied for a patent during 6 years or more[6], we categorize the firm as a persistent innovator. If it applied for a patent in 1-5 years, we consider it an occasional innovator. Firms with no patent applications are non-innovators. The table also reports the corresponding statistics for firms observed in the CIS surveys in Columns 2, 4 and 6. We classify a firm as a persistent innovator for the whole 1997-2008 period if it is reported to be a persistent R&D investor in at least two 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.

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. Corresponding

For instance, the fraction of innovators is 31% in the CIS 2008 data and 54%, on average, in the CIS 2004 and 2006 data.

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

differences are observed between firms classified as occasionally innovative and non-innovators. With respect to growth rates, the descriptive statistics indicate no differences between the two categories of innovative firms, and the average TFP growth rate is highest for non-innovators in Patent sample. The table also reveals that 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, whereas the opposite is true for other services.

4 EMPIRICAL STRATEGY

General approach and hypotheses

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.

With regard to the internal knowledge, three classifications are defined. The first includes firms that do not engage in research and innovation activities (i.e., patent applications in one of the samples, and R&D in the other sample), and we consider their internal accumulated knowledge to be low. Our second group consists of firms that conduct R&I activities occasionally. Their accumulated knowledge is classified as medium. The final category includes firms that persistently engage in renewal efforts resulting in a high level of accumulated internal knowledge. The three categories are labeled I_1, I_2 and I_3, respectively.

For the external knowledge potential of each firm, we identify each firm's access to the supply of knowledge-intensive producer services, which provides a knowledge potential value for every firm[7]. These values allow us to arrange all firms into three categories. The first category includes firms that belong to the lowest third of knowledge potential values. The second is firms that belong to the medium third of knowledge potential values, and the final category consists of firms that belong to the highest third of knowledge potential values. These three categories are labeled K_1, K_2 and K_3.

Based on the two sets of categories, we construct 9 combinatorial categories, as illustrated in Table 4. At one extreme, we find firms with low internal knowledge and low external knowledge potential (IK_{11}), and the firm at the other extreme has high internal knowledge intensity and high external knowledge potential (IK_{33}).

Before we formulate the hypotheses precisely, we should observe that our formulation enables us to clarify the importance of each IK-combination. Therefore, 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 persis-

[7] It should be noted that our knowledge potential indicator also announces the presence of other knowledge sources such as universities, research institutes, high-technology firms and creative capacities.

tent R&I efforts can compensate for a low level of external knowledge potential. Thus, we can contribute to the existing literature about the relative importance of the two knowledge factors in Table 4.

The first hypothesis refers to the combinatorial categories in the I_1-row, comprising firms with a low level of internal knowledge. More formally:

H1: There is no difference in the TFP growth for firms that belong to IK_{11}, IK_{21} and IK_{31}, which implies that the local milieu and the external knowledge potential have no additional impact on firms with low internal knowledge.

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 $IK_{12}<IK_{22}<IK_{32}$. Thus, the growth rate of firms with occasional R&I is an increasing function of access to external knowledge potential.

The third group of firms is involved in persistent R&I efforts (I_3 firms), and the following hypothesis applies for these firms:

H3: There is a difference in the TFP growth for firms that belong to the I_3 classification, such that $IK_{13}<IK_{23}<IK_{33}$. Thus, the growth rate of firms with persistent R&D 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 R&I firms are superior to occasional R&I firms. To accomplish this, we make pairwise comparisons between elements in the I_2 and I_3 columns.

H4: Persistent R&D firms have higher TFP growth than firms with occasional R&D efforts, such that $IK_{13}>IK_{12}$, $IK_{23}>IK_{22}$, $IK_{33}>IK_{32}$. For all categories of location, there is always a positive improvement on TFP growth from more internal knowledge.

Empirical model

To quantify the relationship between TFP and the firm's internal and external knowledge sources, we use an augmented Cobb-Douglas approach specified as a growth model. In doing so, we aim to capture the effect of a particular category of combined knowledge sources on the 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 ordinary 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:

$$\begin{aligned} \Delta lnTFP \quad = \quad & \alpha_0 + [I_i \times K_i]\gamma_i + \beta_1 \Delta lnTFP_{i,t-1} + \beta_2 lnTFP_{i,t-1} + \\ & \beta_3 \Delta lnSIZE_{it} + \beta_4 OWNER_{it} + \beta_5 SECTOR_{it} + \mu_i + \tau_t + \varepsilon_{it} \end{aligned} \tag{1}$$

where i indexes the firm, t the year, I is a vector of innovation indicators, K is a vector of external knowledge indicators, ΔTFP is the annual growth rate of total factor productivity, TFP is the level of total factor productivity, $\Delta SIZE$ is employment growth, and $OWNER$ is corporate ownership. 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 coefficient of interest is γ_i, which determines the response of productivity growth to nine combinatorial categories 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 suggested 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).

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 over-identifying restrictions whereas the Arellano-Bond auto-regressive 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.

5 REGRESSION RESULTS

Table 4 presents estimates of Equation (1) using a two-step dynamic GMM estimator with the total factor productivity growth (TFP) as the dependent variable. Table A.2 in the appendix reports the 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 first panel is labeled the patent panel, and here we use patent applications as a proxy for innovation activity. The second panel is labeled the CIS panel, and in this case the innovation indicator is R&D engagement. 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, 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 IK_{11} in Table 5 as reference group, the estimates in the first panel are small in absolute value and statistically significant only in the first column, showing the GMM estimates for the typical non-innovative firm located in regions with a medium intensity of external knowledge. In this case innovation is proxied by patent and the sign of the coefficient is negative. The first conclusion, however, is that there are no or almost no growth effects from pure and pecuniary spillovers for non-innovators, regardless of the panel, innovation indicator or estimator we consider.

The table reveals three results about rows 4-6 and firms temporarily engaged in innovation activities and with low, medium or high accessibility to outside knowledge in the local milieu. First, the estimates are positive and significantly different from the base-group for the patent panel. Second, the growth rate is markedly higher among temporary innovators in milieus where firms have high access to knowledge sources, compared to identical firms in milieus with medium or low access to external knowledge (0.047 versus 0.015 and 0.017, respectively). Third, the CIS-panel results are similar but weaker, with coefficients that are positive but insignificant or only weakly significant. The final important set of results presented in Table 5 concerns the TFP growth among persistent innovators. Rows 7-9 provide a consistent picture for both samples. First, persistent innovators always have faster TFP growth than other firms, regardless of location. Second, the growth rate for persistent innovators increases with access to external knowledge. Consequently, the size of the estimates is largest for the average persistent R&I firms located in areas with high access to external knowledge. The magnitude of the estimate is 0.14 in the patent sample and 0.112 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 by default fully consistent with the short-run estimates in Columns 1 and 3. 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).

In contrast to the preferred patent panel, the alternative CIS panel contains a smaller proportion of firms with falling productivity, because the panel is a selected group of surviving firms over a 4-7 year period. This difference between the panels is also reflected in the TFP estimate for the CIS panel, which is indeed negative but close to zero (0.154) and insignificant. Turning to other controls, one noteworthy but not unexpected result is that multinational firms have a higher growth rate than other firms, *ceteris paribus*. The TFP growth is notably neutral with respect to firm size, even after controlling for internal and external knowledge.

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 rejects the presence of second-order autocorrelation in the first-differenced residuals in both regressions. Otherwise, the GMM estimator could be inconsistent. The Hansen J-test of over-identifying 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.

Wald test of the predictions

Overall, the results in Table 5 indicate a strong, positive relationship between proximity to knowledge and persistent R&I (innovation activities measured by patent or R&D). To evaluate the quantitative importance of the IK coefficients in detail, we conduct a Wald test on the equality of means in Table 5. The first prediction from our hypotheses H1-H4 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, that the growth rate of firms with occasional R&I is an increasing function of access to external knowledge, is partly confirmed when the patent panel is considered in the H2 portion of Table 5. Temporary innovators in high-access areas are growing faster than temporary innovators located in other places. However, no significant difference exists in the equality of growth means between firms that are occasionally engaged in places with low and medium access to external knowledge. We also find no significant difference in the coefficients with respect to location in the CIS panel. Thus, we cannot confirm hypothesis H2 based on the CIS panel and only partly when we use the patent panel.

We turn to the prediction that the growth rate of firms with persistent R&I is an increasing function of access to external knowledge (H3). The results for the patent panel indicate that persistent innovators in high access (knowledge) regions are growing significantly faster than corresponding firms in both medium- and low-access regions. Moreover, persistent innovators in medium-access places have higher growth rates than persistent innovators in low-access locations.

The CIS panel indicates that persistent innovators in areas with high access to external knowledge are growing significantly faster than the corresponding firms with low access to external knowledge. However, we cannot conclude that the estimation for persistent innovators in places with high access to external knowledge (0.112) is significantly larger than the coefficient for persistent innovators in locations with medium access (0.094) or that the medium-access estimate is greater than the estimate for low access (0.062). The overall assessment based on the estimation of the two panels is that we cannot reject the third hypothesis.

Our final prediction (H4) is that a positive return to improvement of internal knowledge always applies for all categories of location, which implies that persistent innovators outperform occasional innovators in all types of locations. The prediction is strongly confirmed in both of our panels. Table A3 in the appendix indicates that the pooled OLS estimates of Equation (1) produce the same overall results as the more efficient dynamic GMM estimates.[8] The main difference is the sizes of the estimates, which are lower when using the OLS estimator. The estimator suffers from dynamic panel data bias due to serial correlation in the error term 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 environment 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

[8] 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. The results are available upon request.

knowledge.

Although all three regressions suggest economically important effects of internal and external knowledge on TFP growth for persistent innovators, only the preferred GMM model and the OLS estimates also indicate positive effects for temporary innovators in places with high access to external knowledge. However, the latter finding is only relevant for the patent sample. Overall, proximity appears to be more important for innovative firms, consistent with our a priori assumption.

6 CONCLUSIONS

Our study aims to illuminate the separate and combined effect of innovation and potential spillovers from a growth perspective. A significant amount of prior research supports the view that (i) a firm's knowledge is a key competitive asset (Grant, 1996), (ii) continuity of innovation efforts ensures the accumulation of internal knowledge (Dosi and Nelson, 2010), (iii) very few firms, if any, can internally develop all critical knowledge needed for growth (Almeida and Phene, 2012), (iv) a firm's potential for exploiting external knowledge and recombining internal and external knowledge increases with its own knowledge stock (Cohen and Levinthal, 1990), and (v) locational proximity to external knowledge reduces the cost and increases the frequency of contacts with players in a network (Saxenian, 1990). Building on these and similar findings, we construct a simple analytical model that examines how firms exploit internal knowledge in conjunction with external knowledge to gain productivity growth.

We model knowledge inputs in a production function by using a discrete composite variable with nine different combinations of the intensity of knowledge from within and from outside the firm. Internal knowledge is measured by the frequency of national and international patent applications. We have matched patent applications to all 40,524 unique manufacturing and service firms in Sweden with an average of 10 or more employees from 1997 to 2008. A second alternative panel is constructed from an overlapping data set from three Swedish Community Innovation Surveys in 2004, 2006 and 2008 for which 2,738 manufacturing and service firms participated in at least two of the three surveys. In this case, the data are restricted to firms with at least 10 employees during the year of the survey.

To find a proxy for knowledge flow across firms, we identify 35 different Swedish knowledge-intense producer-service industries at the five-digit level in which the share of employees with university degree is above 30 percent. These services include ICT services, engineering R&D and engineering services, financial services, and brokerage and recruitment of manpower.

Applying a dynamic GMM estimator to the data, which also includes extensive firm characteristics on human capital, physical capital, employment, ownership and sector classification, two equations were estimated. The main findings are as follows:

- The local milieu and the external knowledge potential have no additional productivity growth impact on firms with low internal knowledge.
- The growth rate of total productivity is only weakly associated with external knowledge for firms with occasional innovation efforts.
- The growth rate of total productivity is strongly associated with external knowledge for firms with persistent innovation efforts.
- All location categories exhibit improvement of internal knowledge.

Our study provides new empirical knowledge about the systematic differences of firms' capability to benefit from external knowledge. It also suggests a method for capturing and quantifying the extent of knowledge flows across firms. Moreover, the study demonstrates the appropriateness of using the increasingly popular dynamic GMM estimator to control whether productivity and growth results are due to observed heterogeneous characteristics of firms and places or factors such as unobserved heterogeneities or true or false state dependence.

The above findings have implications for both policy and management. With our approach, the results indicate that the benefits of knowledge-intensive local milieus are not uniformly distributed across different types of firms. We find strong effects on TFP growth only for innovating firms and especially for persistent innovators. We do not detect any substantial effect for occasional innovators and no effect at all for 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 leverage effects on 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 a permanent 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 internal mechanisms for creating and maintaining conduits to the external environment that facilitates knowledge flows to the firm. Another issue for future research is to investigate the importance of the corporate ownership. Are multinational firms more efficient at exploiting external local knowledge than other firms? Is there any difference in the ability to benefit from the nearby milieu between domestically owned firms and foreign firms?

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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 Affiliate Firms	0.45	0.38	0.20	0.26	0.08	0.12
Domestic Uninational 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 the 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	3,308	0,47	0,53
26-99	5,860	0,32	0,68
100>	57,458	0,03	0,97
Domestic Non Affiliate Firms	2,427	0,39	0,61
Domestic Uninational 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: Combinatorial categories of internal and external knowledge

	I_1	I_2	I_3
K_1	IK_{11}	IK_{12}	IK_{13}
K_2	IK_{21}	IK_{22}	IK_{23}
K_3	IK_{31}	IK_{32}	IK_{33}

A Appendix

Table 4: Dependent variable: TFP growth, two-step system GMM estimates

Innovation variable	PATENT PANEL		CIS PANEL	
	Short-run	Long-run	Short-run	Long-run
IK_{11}[a]	0.000	0.000	0.000	0.000
IK_{12}	-0.005*	-0.004**	-0.012	-0.010
	(0.00)	(0.00)	(0.01)	(0.01)
IK_{13}	0.002	0.002	0.000	0.000
	(0.00)	(0.00)	(0.01)	(0.01)
IK_{21}	0.017***	0.015***	0.007	0.006
	(0.01)	(0.01)	(0.01)	(0.01)
IK_{22}	0.015**	0.013**	-0.002	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)
IK_{23}	0.047***	0.039***	0.021*	0.018*
	(0.01)	(0.01)	(0.01)	(0.01)
IK_{31}	0.045***	0.038***	0.062**	0.053**
	(0.03)	(0.01)	(0.03)	(0.02)
IK_{32}	0.085***	0.072***	0.094***	0.081***
	(0.03)	(0.02)	(0.03)	(0.03)
IK_{33}	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 Uninational[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 multinationa[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	
Laglimits	(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

[IK_{11}:Non R&I and Low access]; [IK_{12}:Non R&I and Medium access]; [IK_{13}:Non R&I and High access]

[IK_{21}:Occ R&I and Low access]; [IK_{22}:Occ R&I and Medium access]; [IK_{23}:Occ R&I and High access]

[IK_{31}:Pers R&I and Low access]; [IK_{32}:Pers R&I and Medium access]; [IK_{33}:Pers R&I and High access]

Table 5: T-test on the equality of means reported as p-values

	Hypotheses	Patent panel	CIS panel
		t-test	t-test
IK_{13}=IK_{12}	H1	0.00***	0.23
IK_{13}=IK_{11}	H1	0.05**	0.21
IK_{23}=IK_{22}	H2	0.01***	0.09*
IK_{23}=IK_{21}	H2	0.01***	0.21
IK_{22}=IK_{21}	H2	0.79	0.41
IK_{33}=IK_{32}	H3	0.03**	0.38
IK_{33}=IK_{31}	H3	0.00***	0.02**
IK_{32}=IK_{31}	H3	0.01***	0.12
IK_{33}=IK_{23}	H4	0.00***	0.00***
IK_{32}=IK_{22}	H4	0.02**	0.00***
IK_{31}=IK_{21}	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%

[IK_{11}:Non R&I and Low access]; [IK_{12}:Non R&I and Medium access]; [IK_{13}:Non R&I and High access]

[IK_{21}:Occ R&I and Low access]; [IK_{22}:Occ R&I and Medium access]; [IK_{23}:Occ R&I and High access]

[IK_{31}:Pers R&I and Low access]; [IK_{32}:Pers R&I and Medium access]; [IK_{33}:Pers R&I and High access]

Table A.1: Knowledge intense 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 pulling	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 pooled OLS estimates, dependent variables: 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 Uninational^{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

[IK_{11}:Non R&I and Low access]; [IK_{12}:Non R&I and Medium access]; [IK_{13}:Non R&I and High access]

[IK_{21}:Occ R&I and Low access]; [IK_{22}:Occ R&I and Medium access]; [IK_{23}:Occ R&I and High access]

[IK_{31}:Pers R&I and Low access]; [IK_{32}:Pers R&I and Medium access]; [IK_{33}:Pers R&I and High access]