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RESEARCH NOTES AND COMMENTARIES

LEARNING FROM OPENNESS: THE DYNAMICS OF BREADTH IN EXTERNAL INNOVATION LINKAGES

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We explore how openness in terms of external linkages generates learning effects, which enable firms to generate more innovation outputs from any given breadth of external linkages. Openness to external knowledge sources, whether through search activity or linkages to external partners in new product development, involves a process of interaction and information processing. Such activities are likely to be subject to a learning process, as firms learn which knowledge sources and collaborative linkages are most useful to their particular needs, and which partnerships are most effective in delivering innovation performance. Using panel data from Irish manufacturing plants, we find evidence of such learning effects: establishments with substantial experience of external collaborations in previous periods derive more innovation output from openness in the current period. © 2013 The Authors. *Strategic Management Journal* published by John Wiley & Sons Ltd.

INTRODUCTION

Do firms learn from openness in their innovation activity? It has long been recognized that innovation cannot be regarded purely as an internal matter: firms' external linkages or networks may also play a potentially important role (e.g., von Hippel, 1988; Powell, Koput, and Smith-Doerr, 1996; Rothwell *et al.*, 1974). There is also now a considerable body of literature that supports the idea that openness to external knowledge sources helps to boost innovation performance, but that there are limits to the beneficial effects of external links (e.g., Ahuja, 2000; Katila and Ahuja, 2002; Laursen and Salter, 2006; Leiponen and Helfat, 2010; Love and Roper, 2001). We know little, however, about learning effects in this process. This may be in part because most studies of openness in innovation use cross-sectional data (e.g., Freel, 2005; Laursen and Salter, 2006; Leiponen and Helfat, 2010), which do not readily permit analysis of learning effects that occur through time.

There are good reasons to expect such learning effects. Openness to external knowledge partners involves a process of interaction and information

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processing in identifying and selecting appropriate partners, developing routines to interact with them, and constructing management systems to manage the relationships. Such activities are likely to be subject to a learning process, as firms discover through time which knowledge sources and linkages are most useful to their particular needs, which partnerships are most effective in delivering innovation performance, and how best to manage them. In evolutionary terms, this could be seen as the development of improved innovation routines (Nelson and Winter, 1982) or, from a resource-based perspective, the development of new or improved dynamic capabilities in external partnering (Kale and Singh, 2007; Zollo and Winter, 2002). We therefore anticipate that the contribution of openness to innovation in any period will be influenced by the lessons learned from firms' previous experience of external partnering.

Our contribution is to provide an analysis of the benefits of breadth in external innovation linkages with a particular focus on learning effects. More specifically, we examine how previous "openness" affects the impact which current levels of openness have on innovation performance. We base our analysis on an unbalanced panel of Irish manufacturing plants that covers five successive three-year periods spanning the years 1994–2008. We find evidence that establishments that had experience of external collaborations in previous periods do indeed derive more innovation output from openness in the current period, and conclude that this is evidence of learning effects.

CONCEPTUAL FRAMEWORK: LEARNING EFFECTS IN INNOVATION COLLABORATION

Because innovation, and the returns to it, are inherently uncertain, firms have an incentive to develop a number of external linkages simultaneously. In purely statistical terms, since the payoff from any given innovation linkage is unknown in advance, the chance of obtaining benefit from any linkage in a given distribution of payoffs increases as the number of linkages increases. In simple terms, having more linkages increases the probability of obtaining useful external knowledge that can be combined with the firm's internal knowledge to produce innovation (Leiponen and Helfat, 2010). In addition, empirical evidence suggests that knowledge gained from different types of linkages generates complementarities both between external linkages and with firms' internal R&D (Roper, Du, and Love, 2008). Having a number of external linkages of different types therefore increases the likelihood of innovation not only by directly increasing the flow of useful external knowledge, but also by increasing the chances of productive complementarities between external and internal knowledge.

However, there are limits to the value of external linkages for innovation. Search is costly, as is the need to write appropriate contractual agreements for numerous formal linkages, and to maintain these linkages through time. Even where formal contractual issues do not arise, there may be other issues that limit the ability of a firm to pursue large numbers of linkages. These arise from the capacity of management to pay attention to and cognitively process many sources of information, since the span of attention of any individual is limited (Simon, 1947). This attention issue means that, while the returns to additional linkages may at first be positive, eventually the firm will reach a point at which an additional linkage actually serves to diminish the innovation returns to external networking. In their analysis of the breadth of external information sources used by UK manufacturing firms, Laursen and Salter (2006) find that, while the breadth of information sources enhances innovation, beyond some limit the returns to increased breadth of search become negative. A similar result is found for Finnish manufacturing firms by Leiponen and Helfat (2010).

Because they are based on cross-sectional data, these analyses implicitly assume that external linkages have a purely contemporaneous effect on innovation performance. In reality, there is likely to be a temporal dimension to this process. Specifically, there may be a learning process involved in managing external innovation relationships, so that previous experiences shape the relationship between current breadth of linkages and innovation outputs. For example, Powell *et al.* (1996) show that not only are innovation linkages and alliances complementary (i.e., positively linked) within the same time period, but also that firms learn from some links to develop new and more diverse linkages. Collaborative work in one area alerts the firm to the need to access ideas and information from a variety of sources. "An organization simultaneously learns which collaborations to pursue

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and how to function within a context of multiple cooperative ventures" (Powell *et al.*, 1996: 121). The experience gained from collaboration in one field of activity can be used to develop capabilities in collaboration that can be used with other partners, and with a more diverse set of partners. So, firms develop capabilities for interacting with other firms, and learn to do this better through time. Using data from the US biotechnology industry over the period 1990–1994, Powell *et al.* (1996) find support for the hypotheses that experience in collaborations leads to more, and more diverse, forms of collaboration. This provides an important link between learning from external innovation linkages (which can help boost innovation) and learning to use these linkages more effectively over time (which boosts innovation in the future).

This process of organizational learning in managing complex tasks, especially those which occur repeatedly, can not only help improve managers' skills in performing such tasks more effectively through time, but may also develop into a dynamic capability in its own right (Zollo and Winter, 2002). Precisely such a process is described by Kale and Singh (2007) in their work on building firm capabilities through learning in the case of interfirm alliances. They examine the "alliance learning process," defined as "... a process that is directed towards helping a firm (and its managers) learn, accumulate, and leverage alliance management know-how and best practices" (Kale and Singh, 2007: 984). They demonstrate empirically that firms with a stronger alliance learning process have greater alliance success.

In the specific case of breadth of external linkages in the innovation process, learning opportunities present themselves in two ways: first, in *selecting* appropriate partners and, second, in *managing* external relationships.

In terms of selecting appropriate partners, managers may become better at identifying in which external relationships it is worth investing. Since search strategies are to some extent based on previous experience (Laursen and Salter, 2006; Levinthal and March, 1993), it takes time to determine which external linkages are more likely to lead to the most positive payoffs. Through time, therefore, firms may experience larger payoffs from innovation linkages than was the case in the previous period. This is because managers become better at recognizing and selecting productive linkages *ex ante* because they have learned from previous experience.

Managing external linkages can also be a source of learning. This may occur in two ways: the first arises from the development of organizational routines; the second arises from developments in managerial cognition through time.

As enterprises develop mechanisms and routines for managing innovation relationships with external parties, they learn to manage their existing external relationships more efficiently, and therefore obtain higher returns from a given breadth of linkages in subsequent periods. More generally, similar in-house teams might liaise with different types of innovation partners, becoming more effective through time and thus lowering the cost and/or increasing the return from a given breadth of relationships. Precisely such a possibility is suggested by the literature on complementarities between different knowledge sources, where strong positive associations and payoffs are found between the use of internal and external knowledge sources (Cassiman and Veugelers, 2006) and in the use of different external sources (Roper *et al.*, 2008). While this is implicitly a static concept, there is the possibility of dynamic effects here as management teams learn from the process of managing multiple relationships in one period, and are able to apply that learning to manage more efficiently relationships in subsequent periods.

The second mechanism through which learning effects may occur in managing linkages is that previous experience of using external linkages helps to extend the cognitive limits of the management team as they learn to manage more and different forms of innovation linkage. Adner and Helfat (2003) identify "managerial cognition" as an attribute underpinning dynamic managerial capability. As developed by Eggers and Kaplan (2009), this is closely linked to the literature on managerial attention (Ocasio, 1997), in which strategic action is in part shaped by the way managers notice and interpret change, and then make strategic choices. Eggers and Kaplan (2009) demonstrate, for example, that in the context of a radical new telecommunications market, managerial attention (and specifically CEO attention towards the emerging technology) is positively associated with entry into the new market. This can be related to the management of external partnerships, and specifically the breadth of previous linkages. Not only do managers learn to devote more of their limited attention to the most productive relationships, through time they also learn to manage a wider range of external relationships before encountering the cognitive limit at which the innovation returns to an additional relationship becomes negative. Organizations therefore benefit from extending the range of their external knowledge sourcing activities, pushing back the "limits to openness" identified in Laursen and Salter (2006). By implication, this is the mechanism envisaged by Powell *et al.* (1996) in their suggestion that collaborations lead both to more, and more diverse, forms of collaboration. Thus, not only do managers learn to manage existing linkage breadth more efficiently (through the development of routines), they also learn to cope effectively with greater breadth of linkages through time (through improvements in managerial cognition).

The experientially based learning mechanisms outlined above may occur at the level of the individual plant, the firm, or both. Organizational learning involves both creating knowledge and also transferring knowledge within the organization (Argote and Miron-Spektor, 2011). There is therefore also the possibility that learning on external partner selection and management may occur through knowledge transfer between plants within a multiplant firm. Such transfers are likely to be easier where management knowledge can be codified—as in the case of partner search or management routines—but more difficult where knowledge is tacit, as in managerial cognition. Recent research on multinational enterprises suggests that two-way flows of innovation-relevant knowledge between parent companies and their foreign subsidiaries is relatively commonplace (Driffield, Love, and Menghinello, 2010; Singh, 2007). This, in turn, suggests that such firms may be in a position to actively transfer knowledge related to the search, selection, and management of external partners between plants, and that the learning effects arising from this knowledge can be analyzed at the individual plant level. There may also be practical advantages in considering organizational learning at this level. Although strategic decisions may be made at the firm level, they are implemented at the level of the individual plant, and are likely to be based on the product market situation faced by individual plants. This is especially true of large multiplant enterprises. Thus, a firm may use one set of external linkages at one plant and a quite different set at another that is facing a different set of market circumstances, a subtlety that may be missed in firm-level analysis.

The joint effect of the mechanisms discussed above suggests there may be learning effects arising from managing external innovation linkages, such that the benefits of linkages will be greater among establishments with relevant previous experience. This leads to our key hypothesis:

> *Establishments with previous innovation linkages experience higher innovation returns to their current linkage breadth than other establishments.*

DATA AND METHODS

Our empirical analysis is based on data from the Irish Innovation Panel (IIP), which provides information on the innovation activities of manufacturing plants in Ireland and Northern Ireland over the period 1991–2008. Here, due to data limitations in the initial survey, we make use of data covering the 1994–2008 period. This involves five plant-level surveys conducted every three years using similar survey methodologies and questionnaires with common questions. Like the EU Community Innovation Survey (CIS), each of the IIP surveys covers the innovation activities of manufacturing business units over a three-year reference period. The resulting panel is unbalanced, reflecting non-response in individual surveys but also the opening and closure of individual plants: on average there are 1.7 observations per plant in the dataset (see also online supporting information).

As detailed below, our estimation approach allows both for plant-specific fixed effects and for the fact that we are using plant data from an unbalanced panel. We therefore constrain our econometric analysis to include only plants with a minimum of three observations during the survey period. This lowers the number of observations from the initial 3,918 in the full IIP to 1,064 observations that will be used in the econometric analysis. In the case of the reduced sample, the average number of observations per plant is 3.6. The mean values of the key variables used in our econometric analysis are not statistically significantly different between the full sample and the reduced sample.

To allow explicitly for the role of plants that are part of a larger group, and so allow for the possibility of knowledge transfer on external linkage selection and management, we include a variable for the plant's own in-house R&D, and dummy variables for both subsidiary status and for foreign ownership as explanatory variables in estimating the innovation production function. In this way, we capture the possible benefits of group membership in terms of intrafirm knowledge transfer and support for innovation, and possible drawbacks in terms of group strategic direction in terms of, for example, geographic coverage of sales. In common with CIS-type innovation surveys, the estimation sample is restricted only to the "potentially innovative" sample of those plants that have either attempted innovation during the studied period or are at some likelihood of doing so (e.g., Laursen and Salter, 2006; Leiponen and Helfat, 2010). We define the group of attempted or potential innovators as those plants that fulfill at least one of the following criteria: (1) they have undertaken at least some kind of innovation activities in a given period, (2) they report using knowledge linkages in their innovation process, and (3) they report experiencing innovation constraints in a given period that either prevented innovation or reduced its level.

In common with several other innovation surveys, including the CIS, each wave of the IIP considers both the inputs and the outputs of innovation over a three-year period. A common feature of the second to sixth waves of the IIP (covering the 1994–2008 period) is the following question: "Over the last three years, did you have links with other companies or organizations as part of your product or process development?" Plants responding positively to this were then asked to identify the types of external partners with which they collaborated. Eight potential partner types were identified in the questionnaire: customers, suppliers, competitors, joint ventures, consultants, universities, industry-operated laboratories, and government-operated laboratories.[1] This selection of potential linkage partners was made in line with previous research on the benefits of different types of innovation linkages and the complementarities between them (Powell *et al.*, 1996; Roper *et al.*, 2008).

[1] Respondents were also asked to indicate whether they had linkages to "other group companies." This type of linkage is excluded from the current analysis on the basis that this linkage is relevant only to plants that are members of groups rather than all establishments.

In a method analogous to that of Laursen and Salter (2006), we use plants' binary responses to each of these eight questions to define an indicator of the breadth of innovation linkages, which takes values 0–8 depending on the number of different types of innovation partners with which each plant was working. The share of plants with any external linkages varies from 33 percent in 2003–2005 to 45 percent in 1997–1999; the share of plants with a larger number of different types of linkages is significantly lower (Table 1). As we have panel data, we can, in addition to plants' current breadth of openness, identify whether plants used any external linkages in either of the two previous surveys. We use this information to create a dummy variable, which takes value 1 if the plant was engaged in openness prior to the current period and zero otherwise. We then use this to partition the standard breadth measure described above between those plants that had and had not undertaken external innovation linkages in a previous period. Production units with prior innovation linkages had on average 1.8 innovation linkages, whereas plants with no prior linkages had on average 0.6 linkages (Table 2).

Dependent variables

As the dependent variables in our analysis, we use two innovation output measures. The first is the proportion of the plant's total sales (at the end of each three-year reference period) derived from products newly introduced or improved during the previous three years. This variable reflects not only units' ability to introduce innovative products to the market but also their short-term commercial success, and is the most widely used indicator of innovation output in the literature (Laursen and Salter, 2006; Leiponen, 2005; Leiponen and Helfat, 2010; Roper *et al.*, 2008). An average of 20.9 percent of sales was derived from newly introduced or improved products (Table 2). Over the sample, around 60 percent of plants reported introducing such new or improved products. In addition, we employ a measure of total sales revenue derived from new and improved products introduced over the previous three years (Leiponen and Helfat, 2011). Thus, while the first measure indicates the importance of innovative products in the unit's portfolio, the second measures the value of sales of innovative products.

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Table 1. Proportion of plants with different types of external linkages: 1994–2008

	1994–1996	1997–1999	2000–2002	2003–2005	2006–2008
Share of plants with any linkages	0.39	0.45	0.39	0.33	0.38
More than one type of linkage	0.33	0.35	0.29	0.25	0.30
More than two types of linkage	0.20	0.25	0.20	0.15	0.18
More than three types of linkage	0.13	0.16	0.12	0.11	0.08
More than four types of linkage	0.05	0.09	0.06	0.05	0.03
More than five types of linkage	0.03	0.06	0.04	0.04	0.00
More than six types of linkage	0.01	0.02	0.02	0.00	0.00
More than seven types of linkage	0.01	0.01	0.00	0.00	0.00

Source: Irish Innovation Panel, waves 2–6 of the survey are included. $N = 1{,}064$

Table 2. Descriptive statistics

	Mean	Std. dev.
Innovation measures		
Product innovation dummy	0.604	0.489
Proportion of innovative sales (%)	20.904	27.406
Log of innovative sales	4.265	3.716
Linkage breadth measures		
Number of linkages	1.097	1.722
Number of linkages (for plants that reported external linkages in either of the two previous waves of the IIP)	1.825	2.041
Number of linkages (for plants that had no external linkages in either of the two previous waves of the IIP)	0.639	1.293
Prior linkages (0/1)	0.386	0.487
Control variables		
Plant undertakes in-house R&D	0.465	0.499
Plant size (employment)	85.152	217.549
Plant age (years)	34.955	32.183
Subsidiary dummy	0.297	0.457
Externally owned plant	0.225	0.418
Percentage of workforce with degree	9.582	11.579
Public support for innovation	0.243	0.429
Northern Ireland plant	0.431	0.495

Source: Irish Innovation Panel, waves 2–6 of the survey are included. $N = 1{,}064$

Control variables

The IIP also provides information on a number of other plant characteristics, which previous studies have linked to innovation outputs. For example, whether or not plants are undertaking in-house R&D may be important in providing the knowledge inputs for innovation (Crépon, Duguet, and Mairesse, 1998; Love and Roper, 2001) and shaping absorptive capacity (Griffith, Redding, and Van Reenen, 2003). Across the sample, in-house R&D was undertaken by 47 percent of plants (Table 2). Other resource indicators are included to capture the potential effect on innovation of the strength of plants' internal resource base. We include variables that give a quantitative indication of the scale of units' resources—such as employment—as well as other factors that might suggest the quality of the in-house knowledge base, such as subsidiary status, multinationality, and age. Multinationality is included here to reflect the potential for intrafirm knowledge transfer between business units, while vintage is intended to reflect the potential for cumulative accumulation of knowledge capital by older business units or life-cycle effects.

We also include a variable reflecting the proportion of each plant's workforce that has a degree level qualification to reflect potential labour quality impacts on innovation (Freel, 2005; Leiponen, 2005) or absorptive capacity. Studies of the impact of publicly funded R&D have, since Griliches (1995), repeatedly suggested that government support for R&D and innovation can have positive effects on innovation activity both by boosting levels of investment and through its positive effect on organizational capabilities. We therefore include dummy variables to indicate a range of public investments in business units' technological and human resources, largely due to the EU Objective 1 status of Ireland through much of the sample period. A correlation table of key variables is shown in Table 3.

Table 3. Correlation table, variables used in regression analysis

	Proportion of innovative sales (%)	Log of innovative sales	Breadth of linkages	Breadth of linkages squared	Breadth of linkages × high prior	Breadth of linkages × low prior	Breadth of linkages × high prior (five links)	Breadth of linkages × high prior (six links)	Plant undertakes in-house R&D	Subsidiary dummy	Plant size	Plant size squared	Plant age	Externally owned plant	Percentage of workforce with degree
Proportion of innovative sales (%)	1														
Log of innovative sales	0.7251	1													
Breadth of linkages	0.2987	0.3715	1												
Breadth of linkages squared	0.2389	0.3111	0.9313	1											
Breadth of linkages × high prior	0.2303	0.3014	0.802	0.7988	1										
Breadth of linkages × low prior	0.1497	0.1634	0.454	0.3454	−0.1682	1									
Breadth of linkages × high prior (five linkages)	0.0794	0.1806	0.4844	0.5551	0.5605	−0.0727	1								
Breadth of linkages × high prior (six linkages)	0.0908	0.1735	0.4014	0.4777	0.4611	−0.0544	0.814	1							
Plant undertakes in-house R&D	0.3905	0.5238	0.3228	0.2537	0.2544	0.154	0.1412	0.0987	1						
Subsidiary dummy	0.0767	0.2318	0.2114	0.2132	0.1775	0.0847	0.1425	0.1509	0.0833	1					
Plant size	0.0893	0.2327	0.2049	0.1942	0.2114	0.023	0.2519	0.2888	0.1357	0.192	1				
Plant size squared	0.0157	0.0782	0.086	0.0873	0.1024	−0.0108	0.1756	0.2149	0.0419	0.0595	0.9012	1			
Plant age	−0.1229	−0.0336	0.0441	0.0668	0.0467	0.0027	0.0904	0.1135	−0.0176	0.0194	0.1035	0.0696	1		
Externally owned plant	0.1312	0.2554	0.1939	0.1597	0.1708	0.0656	0.1209	0.1292	0.0997	0.6725	0.2315	0.0747	0.0282	1	
Percentage of workforce with degree	0.0701	0.1427	0.1647	0.1249	0.158	0.0369	0.1008	0.0813	0.177	0.2538	0.0861	0.0112	0.0717	0.2694	1
Public support	0.2401	0.3438	0.3397	0.2859	0.2953	0.1206	0.1443	0.1213	0.418	0.0284	0.1294	0.0617	0.0458	0.0736	0.1503

Source: Irish Innovation Panel, waves 2–6 of the survey are included. $N = 1,064$

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Checking for common method bias

It has to be acknowledged that analysis of survey data may suffer from common method variance or bias (CMB). However, it appears that CMB is not a significant problem in our study. We estimate a relatively complicated model (an innovation production function), with dependent variables measured at the end of the period and key explanatory variables measured for each three-year survey period. Also, the answer scales of the questions about the dependent variables and the key explanatory variables are very different. We have checked for CMB more formally by using the Harmon's one-factor test (Podsakoff and Organ, 1986) and the marker variable technique (e.g., Lindell and Whitney, 2001; Malhotra, Kim, and Patil, 2006). Harmon's one-factor test consists to a large extent of running a factor analysis of all key variables in the model. If the first unrotated factor accounts for a relatively small share of the total variance (not more than 50 percent), the implication is usually that CMB is not likely to be a significant problem. Harmon's one-factor test suggests in our case that one single factor explains only about 27 percent of total variation of the main variables in our model.

Some authors (Podsakoff *et al.*, 2003) argue that Harmon's test may be insufficient to test for the presence of CMB. Therefore, we have implemented also the marker variable technique for spotting the potential CMB problem (Lindell and Whitney, 2001). This approach is based on comparison of pairwise correlations in the case of key variables in the dataset. In the case of this technique, a "marker variable" is sometimes identified as a variable that is theoretically unrelated to at least one variable in the study. Alternatively, where a marker variable cannot be identified *a priori*, the variable with lowest correlation with other variables is chosen as the "marker." In this last case, the smallest positive correlation in the correlation matrix of variables used in the study is considered as a proxy for CMB. Based on both alternatives of the marker variable technique, there appears to be no reason to suspect significant CMB in our analysis.[2]

Estimation

We estimate two forms of the innovation production function. Let $INNOV_{it}$ be an innovation output indicator (for plant i at survey period t) and FC_{it} be the vector of plant characteristics that we use to control for other influences on innovation outputs. The first form, which provides benchmark estimates, is a standard innovation production function incorporating breadth and breadth-squared variables analogous to Laursen and Salter (2006). Let B_{it} represent the breadth of plants' collaborative activity (i.e., count of different types of external linkages), then this innovation production function with time effects (τ_t), plant-specific fixed effects (π_i), and idiosyncratic errors (ϵ_{it}) can be written as:

$$INNOV_{it} = \delta_0 + \delta_1 B_{it} + \delta_2 B_{it}^2 + \delta_3 FC_{it} + \tau_t + \pi_i + \epsilon_{it}. \tag{1}$$

We anticipate that $\delta_1 > 0$ and $\delta_2 < 0$, reflecting the inverted U-shaped relationship between innovation outputs and breadth found in previous research (Laursen and Salter, 2006; Leiponen and Helfat, 2010). To capture potential learning effects and test the central hypothesis, we then partition both B_{it} and its square between plants that engage in prior collaborative linkages and those and that do not. Let PR_{it} take value 1 if a plant was engaged in prior collaborative linkages and value 0 otherwise; then Equation 1 can be rewritten as:

$$\begin{aligned} INNOV_{it} = \delta_0 &+ \delta_{11} PR_{it} \times B_{it} + \delta_{12}(1 - PR_{it}) \\ &\times B_{it} + \delta_{21} PR_{it} \\ &\times B_{it}^2 + \delta_{22}(1 - PR_{it}) \times B_{it}^2 \\ &+ \delta_3 FC_{it} + \tau_t + \pi_i + \epsilon_{it} \end{aligned} \tag{2}$$

Clearly if the coefficients of the variables $PR_{it} x B_{it}$ and $(1 - PR_{it}) x B_{it}$, and those of their squared terms, are not significantly different from each other, then the relationship between innovation and current linkages does not depend on prior linkages. Therefore, we reject the key hypothesis if we cannot reject the joint equality test of $\delta_{11} = \delta_{12}$ and $\delta_{21} = \delta_{22}$. We also test how the breadth of

[2] One marker variable we tried was the indicator of government support to exports. The lowest correlation of this variable with the ones in Model 1 was with age of the plant (0.0049). (There were several other variables with similar low correlation with government support to exports.) Taking this correlation as a measure of the CMB and subtracting it from the other pairwise correlations does not significantly affect the correlations between the variables used in our regression analysis, in Equation 1 or 2. Other marker variables yielded similar results.

previous collaborative linkages influences the returns to current linkages by estimating Equation 2 for each value of PR_{it} from 1 to 8, i.e., from the lowest to the highest values of prior linkage breadth.[3] This shows precisely whether different values of prior linkage breadth result in learning effects, and whether there is some optimal level of prior breadth.

The ideal estimation approach would allow us to account for unobserved heterogeneity (i.e., plant-specific, time-invariant unobserved factors of innovation performance) and to check whether the inverted U-shaped relationship between breadth and innovation performance persists if we concentrate on within-plant effects. We therefore employ a fixed effects OLS (ordinary least squares) model in estimating Equations 1 and 2, which allows us not only to determine the effect of prior openness but also to control for unobserved heterogeneity in a manner not possible in cross-sectional studies (cf. Leiponen and Helfat, 2010: 227).[4]

RESULTS

The results of estimating Equations 1 and 2 are given in Tables 4 and 5. In each case, Model 1 employs a specification of the knowledge production function analogous to that used in Laursen and Salter (2006), with current breadth of linkages and its squared term as the key explanatory variables. While we find evidence that linkage breadth is associated with higher innovation outputs, unlike Laursen and Salter, we find no evidence of an inverted U-shaped relationship (the squared term has an insignificant coefficient).

We next investigate whether the presence of previous openness changes the effects of current linkage breadth on the innovation output of the plant. This is done by estimating Equation 2. However, it may be the case that plants need to reach a certain level of prior openness before the beneficial learning effects materialize. Learning which linkages pay off in innovation terms, and therefore learning to which ones it is worth devoting valuable management attention, may not only take time, but may also be a function of the *breadth* of previous linkages. We therefore perform a number of separate estimations setting the prior openness dummy equal to 1 if the plant had at least one, two, three, four, five, or six knowledge linkages, respectively, during at least one of the two previous periods. This allows us to determine precisely what extent of previous breadth of innovation collaboration is required for learning effects to occur. Results are shown in Models 2–5 of Tables 4 and 5.

The results suggest that learning effects do indeed occur, but only where there is substantial linkage breadth in previous periods. For example, where plants have at least one previous linkage (Model 2), the Wald tests suggest that there is no significant difference between plants with and without prior linkages for either dependent variable. The same is true for plants with at least two or three prior types of knowledge linkage (results not shown—available on request). However, the situation is very different for plants that have at least four types of previous linkage (Models 3–5), where there starts to be evidence of some benefit from the existence of prior linkages. In particular, for plants with at least five types of previous linkage and above (Models 4 and 5), there is statistical evidence of the significant role of prior breadth of openness: the Wald tests of the joint condition that $\delta_{11} = \delta_{12}$ and $\delta_{21} = \delta_{22}$ in Equation 2 is rejected for the first dependent variable, and in the case of the second (log of innovative sales), only plants with substantial prior linkage breadth show enhanced levels of innovation. Thus, plants with at least five types of prior linkages have a significantly greater innovation return to their current linkage breadth than those with lower prior linkages, and this effect persists for six-plus types of linkage.[5]

Two other results are worthy of note. First, for both dependent variables, the benefits of prior linkage breadth increases consistently as the number of previous linkage types increases. Second, in both cases, there is some evidence of an inverted U-shaped effect of linkage breadth once at least

[3] In practice, it was not possible to perform estimations for prior breadth involving seven or eight linkages as the number of observations of this type was extremely small (see Table 1).

[4] A Hausman test indicated that fixed effects estimation was preferred to its random effects equivalent. For example, the Hausman test statistic in testing the fixed effects vs. random effects specification in Model 1 in Table 4 is 30.11 (p-value 0.007).

[5] We note that there appears to be evidence suggesting statistically significant benefits of having larger breadth of current linkages also in the case of plants with no prior external linkages (see Model 2 in Table 4), but these benefits are still significantly below those obtained by plants with high levels of prior linkages.

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Table 4. The role of external linkage breadth in innovation (fixed effects estimation): share of sales from new or improved products as the dependent variable

	Share of sales from new or improved products				
Dependent variable	(1) Model 1	(2) Model 2, prior = 1 if at least one linkage	(3) Model 3, prior = 1 if at least four linkages	(4) Model 4, prior = 1 if at least five linkages	(5) Model 5, prior = 1 if at least six linkages
R&D conducted in-house	13.819***	13.911***	13.836***	13.542***	13.795***
	(2.419)	(2.422)	(2.420)	(2.411)	(2.394)
Breadth of linkages	3.417**				
	(1.497)				
Breadth of linkages squared	-0.151				
	(0.279)				
Breadth of linkages × high prior		3.576*	5.265*	11.029***	13.799***
		(1.915)	(2.541)	(3.227)	(4.017)
Breadth squared × high prior		-0.118	-0.305	-1.268*	-1.229*
		(0.333)	(0.425)	(0.543)	(0.685)
Breadth of linkages × low prior		4.600***	3.196*	1.800	2.233
		(2.136)	(1.729)	(1.636)	(1.559)
Breadth squared × low prior		-0.566	-0.142	0.191	0.068
		(0.487)	(0.349)	(0.319)	(0.299)
Employment (no.)	0.058	0.059	0.057	0.064*	0.075*
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Employment squared	-0.058	-0.621	-0.588	-0.656	-0.802*
	(0.413)	(0.415)	(0.413)	(0.412)	(0.420)
Establishment age (years)	-0.015	-0.017	0.015	0.025	0.038
	(0.116)	(0.116)	(0.117)	(0.117)	(0.118)
Subsidiary dummy	-11.880***	-11.802***	-11.415***	-11.062***	-10.935***
	(4.233)	(4.240)	(4.251)	(4.235)	(4.219)
Externally owned	-0.040	-0.336	-0.268	-0.257	-1.480
	(3.793)	(3.827)	(3.799)	(3.787)	(3.759)
Workforce with degree (%)	-0.188	-0.190	-0.194	-0.186	-0.191
	(0.126)	(0.126)	(0.126)	(0.125)	(0.124)
Government support for product innovation	-1.431	-1.331	-1.150	-1.030	-0.803
	(2.517)	(2.519)	(2.253)	(2.513)	(2.488)
Constant	16.127***	16.544***	16.085***	14.216***	14.775***
	(4.501)	(4.515)	(4.519)	(4.553)	(4.609)
Observations	1064	1064	1064	1064	1064
R-squared (within)	0.113	0.116	0.116	0.124	0.141
F-test (p-value)	5.67	5.06	5.07	5.45	5.96
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes and sources: Estimation by OLS with plant-level fixed effects. Standard errors in parentheses. Joint F-test statistic (and corresponding p-value) of hypothesis that $\delta_{11} = \delta_{12}$ and $\delta_{21} = \delta_{22}$ is 0.82 ($p = 0.439$) in Model 2, 0.85 ($p = 0.430$) in Model 3, 3.58 ($p = 0.029$) in Model 4, 7.92 ($p = 0.0004$) in Model 5.
Irish Innovation Panel, waves 2–6 of the survey are included.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

five previous linkage types is reached. This suggests that, at least where plants already have substantial experience of external linkages, the diminishing returns to increased breadth observed in cross-sectional studies (Laursen and Salter, 2006; Leiponen and Helfat, 2010) are at least partly a within-plant effect, and not exclusively an across-plant effect.

The coefficients of other control variables in the knowledge production function are largely unsurprising. Plants conducting R&D report on average 14 percentage points higher share of sales of new and improved products than plants without R&D, and larger plants tend to have higher levels of innovative sales. The negative effect of subsidiary status is of some interest. Since the

Table 5. The role of external linkage breadth in innovation (fixed effects estimation): log of innovative sales as the dependent variable

	Log of innovative sales				
Dependent variable	(1) Model 1	(2) Model 2, prior = 1 if at least one linkage	(3) Model 3, prior = 1 if at least four linkages	(4) Model 4, prior = 1 if at least five linkages	(5) Model 5, prior = 1 if at least six linkages
R&D conducted in-house	2.368***	2.360***	2.369***	2.350***	2.359***
	(0.308)	(0.309)	(0.309)	(0.308)	(0.308)
Breadth of linkages	0.289				
	(0.186)				
Breadth of linkages squared	-0.018				
	(0.035)				
Breadth of linkages × high prior		0.164	0.338	0.874**	0.918*
		(0.237)	(0.315)	(0.390)	(0.498)
Breadth squared × high prior		-0.00003	-0.031	-0.121*	−0.101
		(0.041)	(0.051)	(0.065)	(0.083)
Breadth of linkages × low prior		0.422	0.241	0.121	0.205
		(0.275)	(0.220)	(0.206)	(0.198)
Breadth squared × low prior		-0.043	-0.005	0.022	-0.001
		(0.063)	(0.045)	(0.041)	(0.038)
Employment (no.)	0.014***	0.014***	0.014***	0.015***	0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Employment squared	-0.104*	-0.102*	-0.102*	-0.107*	-0.113**
	(0.050)	(0.050)	(0.05)	(0.050)	(0.050)
Establishment age (years)	-0.010	-0.011	-0.010	-0.006	-0.007
	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Subsidiary dummy	-0.659	-0.677	-0.676	-0.631	-0.570
	(0.525)	(0.526)	(0.528)	(0.527)	(0.528)
Externally owned	-0.249	-0.206	-0.236	-0.225	-0.315
	(0.468)	(0.474)	(0.470)	(0.469)	(0.471)
Workforce with degree (%)	-0.015	-0.015	-0.015	-0.015	-0.015
	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)
Government support for product innovation	0.089	-0.094	-0.087	-0.069	-0.067
	(0.312)	(0.312)	(0.314)	(0.312)	(0.312)
Constant	2.823***	2.812***	2.802***	2.622***	2.622***
	(0.569)	(0.571)	(0.572)	(0.578)	(0.578)
Observations	962	962	962	962	962
R-squared (within)	0.166	0.167	0.166	0.172	0.170
F-test (p-value)	7.59	6.68	6.64	6.89	6.79
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Notes and sources: Estimation by OLS with plant-level fixed effects. Standard errors in parentheses. Joint Wald chi^2 test statistic (and corresponding p-value) of hypothesis that $\delta_{11} = \delta_{12}$ and $\delta_{21} = \delta_{22}$ is 0.36 ($p = 0.695$) in Model 2, 0.11 ($p = 0.893$) in Model 3, 1.80 ($p = 0.167$) in Model 4, 1.12 ($p = 0.328$) in Model 5.
Irish Innovation Panel, waves 2–6 of the survey are included.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

estimates are fixed effects, reflecting within-plant variation, these results must reflect the impact of acquisition of previously independent plants that have become subsidiaries of a larger group. Interestingly, this negative effect occurs only for the share of innovative sales variable, not the level of innovative sales, suggesting that when such an acquisition occurs the sales of the acquired plants' portfolio of older products expands faster (or decreases less) than its newly introduced products. This effect applies only to plants acquired by domestically located groups; there is no effect of acquisition by foreign firms (the externally owned coefficient is consistently insignificant).

Robustness check

The results discussed above suggest that plants with substantial previous experience (i.e., breadth) of innovation linkages obtain greater innovative returns to existing linkages. As a robustness check, we consider whether the observed effect of previous linkages is merely the direct effect of lagged knowledge linkages (i.e., a simple dynamic effect), rather than a learning effect *per se*. We therefore perform an estimation that contains current breadth of linkages and its square, their lagged equivalents, and interaction terms between the current and lagged values. For both dependent variables, the coefficients on lagged breadth and all the interaction terms are consistently insignificant,[6] suggesting that the observed results do indeed reflect the impact of substantial prior linkages on current linkages, consistent with the interpretation above.

CONCLUSIONS AND DISCUSSION

This paper explores one aspect of openness in the organization of firms' innovation activities—how external linkages help shape innovation outcomes. In particular, we explore how business units learn from prior openness, thus providing a temporal dimension to the link between external relationships and innovation. We find that having linkages in previous time periods has a positive effect on the relationship between current linkage breadth and innovation, suggesting that there are learning effects present in terms of innovation linkages. However, breadth matters in previous time periods, as it does in the present period: there is a statistically significant difference in the relationship between current openness and performance only for establishments that already had more than four different types of linkage in a previous period.

Overall, our results suggest support for the concept of learning effects from previous linkages. Management teams learn from the process of selecting and/or managing multiple relationships in one period, and are able to apply that learning in subsequent periods. This, in turn, has implications for the open innovation paradigm and for research on innovation generally. Although the open innovation paradigm, at least implicitly, deals with openness through time (Chesbrough, 2006), most empirical studies rely on cross-sectional data to examine the link between openness and innovation. Our results suggest there may be a double benefit from openness in innovation: openness increases innovative performance in the current period (as previous studies suggest), and also provides the basis for learning effects, which increase the benefits of future openness. This suggests that future research on open innovation should pay more attention to the time dimension in examining how openness affects innovation.

The implications for management arise from a deeper understanding of the temporal dimension of the relationship between external linkages and innovation. The benefits of such linkages do not derive solely from their current impact on innovation but also from the knowledge gained in the learning process that takes place through time. At the level of the individual plant, this suggests that investing time in learning how to manage such linkages, and adopting a strategic view of those linkages that have the highest returns, can have significant payoffs in terms of future innovation. Intrafirm transfers of management knowledge relating to the selection and development of external innovation linkages may have similarly positive payoffs. Capturing these benefits—maximizing the value of potential learning—will require some consistency in the allocation of responsibility for developing and managing external innovation linkages within an organization. Where this can be done, our results suggest that managing external relationships can itself develop into the basis for a dynamic capability, with implications for future performance (Kale and Singh, 2007; Zollo and Winter, 2002).

Limitations and future research

It has to be mentioned that the results presented here show associations of prior and current linkages on one hand and current innovation output of the plant on another. Although we have introduced a time dimension into these relationships, care is necessary in interpreting the associations as strict causal effects. For example, it may be that intensity of innovation activities in the past affects the firm's willingness to invest in knowledge linkages and to look actively for ways to involve knowledge partners in their innovation process. There may also be time-varying unobserved variables that directly affect both innovation performance and the breadth of innovation-related linkages. We

[6] These estimations are available on request.

have employed fixed-effects panel data techniques, which help mitigate the effect of (time-invariant) unobserved heterogeneity, and have conducted relevant robustness checks; nevertheless, we cannot absolutely discount these effects.

Future research might usefully explore the precise nature of the apparent learning effects identified above. For example, do the learning effects occur mainly through better selection of collaborative partners or through improved management of external relationships? Do different types of linkages have different learning effects? It is likely that research to answer these questions will come from more in-depth analysis of individual firms' innovation and linkage activity as well as from broad survey-based datasets.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. Description of the Irish Innovation Panel.