Papers in Evolutionary Economic Geography

11.05

When do global pipelines enhance knowledge diffusion in clusters?

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Abstract

Recent studies have stressed the role played by global pipelines in fostering cluster growth and innovativeness. This paper develops a formal model investigating when global pipelines contribute to increase local knowledge, depending on various cluster characteristics such as size, knowledge endowment and ease of internal knowledge transmission. This model is an extension of Cowan and Jonard's 2004 model in which we introduce the concept of cluster and a role for spatial proximity in knowledge diffusion. We find that there is a natural tendency of actors within global pipelines to act as *external stars* rather than *knowledge gatekeepers*. Global pipelines are beneficial for cluster knowledge accumulation only if the cluster is either characterized by a high quality local buzz or is small and weakly endowed in terms of knowledge.

Key Words: knowledge gatekeepers, clusters, knowledge diffusion.

JEL Codes: R11, O33, D83, C63.

1. Introduction

In the literature, there is wide agreement about the ease with which knowledge diffuses in spatial clusters of similar and related economic activities. Many studies have underlined the role of personal contacts as an effective way of transferring knowledge within clusters (Becattini, 1990; Asheim, 1994; Audretsch and Feldman 1996; Feldman, 1999; Maskell and Malmberg, 1999). Since knowledge is incorporated in the skills of individuals, learning mainly occurs through personal interaction, the necessary and to some extent sufficient conditions of which are physical proximity and local embeddedness. The intensity of knowledge flows has been identified as one of the main general explanations for the existence of clusters as well as for their economic success (Maskell and Malmberg, 2007).

However, it has also been pointed out that within clusters there is a risk of lock-in and that too much proximity may lead to a lack of new ideas and information, drawing local actors towards inferior solutions (Uzzi, 1996; Boschma, 2005). To avoid the risk of becoming too narrowly focused, being unable to shift towards novelties, clusters also need to maintain linkages with external actors (Bathelt et al., 2004). Therefore, it may be said that successful clusters are those that are characterized by a dense local network and, at the same time, are involved in *global pipelines* (Bathelt et al., 2004; Storper and Venables, 2004).

The recognition of the importance of both external and internal sources of knowledge leads to questions about the structure of knowledge relations between actors within and across clusters. Some recent empirical studies have stressed the important role played by *knowledge gatekeepers*, defined as those actors who have strong knowledge bases and maintain tight external links, being also willing to diffuse their knowledge within the cluster (Giuliani and Bell, 2005; Morrison, 2008; Graf, 2011). The presence of knowledge gatekeepers can be considered as a condition for avoiding the risk of lock-in and, at the same time, exploiting the advantages of proximity for diffusing external knowledge to a large variety of local actors.

Nevertheless, as suggested by the literature on knowledge barter (Rogers, 1982; von Hippel, 1987), externally connected firms are not always willing to share their knowledge with local firms, since their attitude depends on reciprocity with other members of the cluster (Morrison, 2008). It may be that firms with a stronger knowledge base and tight external connections do not have any incentive to interact with the majority of local less knowledgeable firms. In such contexts, globally connected actors would act more as *external stars* than as gatekeepers (Morrison and Rabellotti, 2009).

In this paper, we aim at contributing to the existing literature, which is mainly empirical or conceptual, with a formal model investigating when global pipelines contribute to increase local knowledge depending on various cluster characteristics such as size, knowledge endowment and ease of internal knowledge transmission. The model is an extension of Cowan and Jonard's (2004), in which we introduce the concept of cluster and a role for spatial proximity in knowledge diffusion.

In line with the existing debate (Bathelt at al., 2004), the perspective of the paper is *normative*, studying how the characteristics of the cluster affect its performance in terms of knowledge acquisition, while not considering the *positive* dimension, i.e. the individual incentives actors have in setting up and maintaining connections within and outside the cluster.

The main result of our study is that, although there is a natural tendency for more knowledgeable actors (here called *experts*) to behave as external stars, their global pipelines are beneficial for increasing the cluster level of knowledge when some conditions apply: i) the cluster is characterized by a high quality local buzz (i.e. social and cultural homogeneity, which facilitates the internal circulation of knowledge), so that there is the internal capacity to take advantage of the knowledge that global pipelines bring into the system; ii) the cluster is small and weakly endowed in terms of knowledge, so that there are no internal substitutes to the learning opportunities coming from outside. In these cases, experts play the role of knowledge gatekeepers, so that their external connections are socially beneficial.

The paper is organized as follows: Section 2 reviews the recent literature on knowledge diffusion in clusters, with a particular emphasis on the role of global pipelines; Section 3 introduces the model in detail; Section 4 reports the results from the numerical simulations and Section 5 concludes.

2. Clusters and knowledge diffusion: internal linkages and global pipelines

Clusters are spatial configurations in which collective learning processes are enhanced by frequent opportunities for formal and informal interactions among firms along horizontal and vertical linkages (Maskell and Malmberg, 1999; Maskell, 2001; Capello and Faggian, 2005). The horizontal dimension of a cluster consists of contacts among firms producing similar products and therefore competing among themselves. These interactions, mainly based on rivalry, may enhance knowledge through unintended spillovers derived from monitoring, comparing and imitating, leading to product differentiation and variation (Bathelt et al., 2004) or through informal knowledge trading among experts (von Hippel, 1987; Carter, 1989; Lissoni, 2001). Quite differently, vertical relations are usually intentional and purposeful linkages based on cooperation with suppliers, service providers and customers (Lundvall, 1992), leading to strong division of labour and specialization.

The intensity of traded and untraded interdependencies among people and firms generates a sort of *local buzz*, which is made up of a lot of information, inspiration and news, benefitting every actor within the cluster by *just being there* (Gertler, 1995; Storper and Venables, 2004). The existence of trust (Maskell et al., 1998) and the natural development of a similar language and common culture (Lawson and Lorenz, 1999) facilitate the access and understanding of the local buzz by firms sharing the same location.

It must also be said that, although taking advantage of the buzz does not require specific investments, the same sort of buzz is not created in every cluster nor is it equally relevant for every firm in the cluster (Bathelt at al., 2004). If the knowledge base of local actors is weak, it is possible that the shared information does not contribute in any significant way to enhance collective learning (Morrison and Rabellotti, 2009). Moreover, some scholars have stressed potential harmful effects of too much proximity (Boschma, 2005) and overembeddedness (Uzzi, 1996) within clusters. In particular, it has been argued that too much specialization might widen the difference in knowledge bases across firms and, in so doing, hinder interactions (Maskell, 2001). Moreover, intensive and recurring cooperation and knowledge sharing might reduce the benefits of exchanging knowledge, since firms become too similar. Decrease in variation implies a risk of *lock-in*, with firms within clusters getting stuck in apparently successful routines and specializations, without recognizing the changes and opportunities emerging in new markets and technologies (Lambooy and Boschma, 2001; Martin and Sunley, 2007).

Clusters can avoid lock-in through an endogenous process of knowledge creation and recombination (Hassink, 2005), requiring local bridging of previously unconnected knowledge networks (Glucker, 2007). In order to do so, firms need to establish external linkages within global production and innovation networks (Scott, 1988; Camagni, 1991; Becattini and Rullani, 1996). Accordingly, a stream of the literature has focused attention on external linkages, which might provide complementary assets, new market relationships as well as access to novel and non-redundant information. External connections can take place through different channels: for example through migrant communities of knowledge experts (Saxenian, 2006), through multinationals functioning as local brokers (Markusen, 1996; Glucker, 2007), through linkages within international networks (Amin and Thrift, 1992) or strategic partnerships (Owen-Smith and Powell, 2004). In sum, all these connections allow external knowledge to be combined with local and mostly idiosyncratic knowledge in novel ways (Nonaka and Takeuchi, 1995; Becattini and Rullani, 1996; Lazerson and Lorenzoni, 1999).

Furthermore, as suggested by Bathelt et al. (2004) in their buzz-pipeline model of cluster competitiveness, it is important to underline that external knowledge flowing from globally connected actors (i.e. global pipelines) to the cluster does not necessarily spill over to each cluster member. If external linkages are too strong: '*less attention is being paid to local communication and information and people are less interested to participate in local broadcasting.*' (Bathelt et al., 2004, 48).

Global pipelines yield positive outcomes if boundary spanners or knowledge gatekeepers are present. These actors invest in setting pipelines to distant actors, upgrading their stock of knowledge, renovating their routines and, at the same time, they maintain tight internal linkages and, in so doing, enhance variation in the local knowledge community (Kauffeld-Monz and Fritsch, 2007; Morrison, 2008; Rychen and Zimmerman, 2008; Graf, 2011). In analogy with the gatekeepers in R&D laboratories (Allen, 1977), their role is in identifying external sources of new relevant knowledge, translating and adapting it for those actors who are unable to establish external connections (Morrison, 2008). Acting as boundary spanners, they need to have a strong relational capital together with a strong knowledge base (Tushman, 1977). In other words, they reconcile the conflict between embeddedness and structural holes, facilitating the formation of a network structure that combines the benefits of local clustering (i.e. high trust and cooperation) with the existence of short paths to external sources (i.e. rapid and facilitated access to novel information) (Verspagen and Duysters, 2004).

In clusters, the gatekeeper functions properly when some conditions hold. First, the presence of some good quality buzz is necessary for local firms to benefit from the externally acquired knowledge (Bathelt et al., 2004). Second, externally connected firms are intentionally disposed to share their knowledge with local firms if the other members of the cluster can reciprocate the exchange with valuable information, as suggested by the literature on knowledge barter (Rogers, 1982; von Hippel, 1987). As shown in Morrison and Rabellotti (2009), if clusters are characterized by a very uneven distribution of knowledge, the few firms with a stronger knowledge base that establish external connections do not have the right incentive to interact with the majority of local less knowledgeable firms. In such contexts, globally connected actors act more as *external stars* than gatekeepers (Giuliani and Bell, 2005). In other cases, it has been shown that brokers can be very selective as knowledge gatekeepers, by only sharing their external connections within a closed club of local partners (Giuliani, 2007; Morrison, 2008). Finally, gatekeepers, and firms in general, are able to maintain linkages only with a limited number of external actors because their establishment and maintenance require substantial time and effort (Grabher, 2001).

From what has been said so far, some final remarks can be drawn. First, knowledge generation and diffusion is highly localized and firms in clusters can easily and meaningfully take advantage of the local buzz. Second, to avoid lock-in firms in clusters need to establish global pipelines. Third, external linkages enhance cluster development if knowledge gatekeepers are present along with some conditions/incentives for them to operate effectively. In this paper, by developing a formal model we aim to investigate some of those conditions that influence how global pipelines impact on cluster performance in terms of knowledge acquisition.

3. The model

Our model builds on a recent stream of theoretical literature, which investigates the relationship between networks and the creation and diffusion of knowledge (Cowan and Jonard, 2004; Morone and Taylor, 2004; Ozman, 2007; Cassi and Zirulia, 2008). In particular, it is an extension of Cowan and Jonard (2004), introducing a specific role for clusters and geography into their framework of diffusion of different types of knowledge through a barter process among agents.

3.1.The model set-up

Heterogeneous agents populate the economy. These agents can be interpreted as firms or individuals working within firms (e.g. technicians). Agents are located in different clusters, i.e. they are (exogenously) located in space. Formally, there is a set N of agents (n is the number of agents), partitioned in two clusters (c = 1, 2 is the index for clusters), so that $N_c \subset N$ is the set of agents belonging to cluster c (n_c is the number of agents in the cluster).

In each period t, each agent i is associated with a vector of knowledge $V_i(t) \in \Re_+^K$, where the K components correspond to different categories of knowledge. Then, $V_{i,k}(t)$ is the level of knowledge in category k for agent i at time t.

At t=0, each agent is endowed with a given stock of knowledge in each category. There are two groups of actors: *experts*, who are characterized by a high level (on average) of knowledge and *non-experts*, characterized by a lower level of knowledge than experts. Formally, at t=0 for each category the level of knowledge of non-experts is drawn randomly (with uniform probability) from the interval [0; 1], while for experts the level of knowledge is assigned in the same way, except for one type, in which they possess a level of knowledge equal to 10.

A network G characterizes the economic system. For each agent, the network identifies the subset of other agents with whom it is directly connected and can exchange knowledge through bilateral face-to-face interactions, according to the mechanism described below (see 3.1.2). The network is exogenously given at $t=0$ and is kept fixed over time. This implies that agents are *embedded* in a web of pre-existing social relations (Granovetter, 1985), which determine the set of their possible partners, whereas the actual use of these linkages depends on the agents' opportunities to increase their knowledge endowment.

Two dimensions characterize the linkages: the type of agents involved – *experts* (E) and *non-experts* (NE) – and the spatial geography – *within* (W) and *between* (B) *clusters*. By crossing them, we obtain six different types of pairs and with each combination we associate a probability of existence of a link between two nodes. Therefore, the following vector (called $p \equiv [p_{EEW}\ p_{EEB}\ p_{ENEW}\ p_{ENEB}\ p_{NENEW}\ p_{NENEB}]$) of six probabilities randomly generates the network *G*:

i) p_{EEW} : probability that a link exists between two experts in the same cluster;

ii) p_{EEB} : probability that a link exists between two experts in different clusters;

iii) p_{ENEW} : probability that a link exists between one expert and one non-expert in the same cluster;

iv) p_{ENEB} : probability that a link exists between one expert and one non-expert in different clusters;

v) p_{NENEW} : probability that a link exists between two non-experts in the same cluster;

vi) p_{NENEB} : probability that a link exists between two non-experts in different clusters.

In order to introduce into the model the idea that spatial proximity facilitates social links and therefore social relations tend to be geographically bounded (Boschma, 2005), we assume that:

$$p_{EEW} \geq p_{EEB};\ p_{ENEW} \geq p_{ENEB};\ p_{NENEW} \geq p_{NENEB}.$$

In other words, given the types of agents in the pair (experts vs. non-experts) and following the literature discussed in the previous section, we assume that a link between two actors is more likely to exist if they are located in the same cluster than in different ones.

3.1.2 Knowledge barter and the evolution of clusters

At each $t>0$, the following process takes place. One link (i.e. two directly connected agents *i* and *j*) is picked at random, with each link having the same probability of being drawn. The randomly selected agents *i* and *j* are the only ones who can exchange knowledge at time *t*. The level of knowledge in category *k* that agent *i* can reach after exchanging knowledge with *j* is given by:

$$V_{i,k}^{B}(t+1)=V_{i,k}(t)+\alpha_r \max\{V_{j,k}(t)-V_{i,k}(t),0\} \qquad (1)$$

Equation (1) (with a symmetric one holding for *j*) reads as follows. Agent *i* can learn from *j* (i.e. he/she can increase his/her knowledge level in *k*) only if *j* knows more than *i*, meaning that $V_{j,k}(t) > V_{i,k}(t)$. If that is the case, *i* increases his/her stock in category *k* by a fraction $\alpha_r \in (0,1)$ with *r=W,B*.

We denote with α the vector [α_W; α_B], measuring the ease of knowledge transfer through face-to-face interactions within and between clusters. In other words, *α* captures all those factors influencing knowledge diffusion, such as culture, trust and communication codes. In order to further account for spatial proximity in the model, we assume that $\alpha_W \geq \alpha_B$. Therefore, given the knowledge profiles of the pair and their learning opportunities, knowledge is more easily transferred within clusters than between clusters. This captures the effect of local buzz (Bathelt et al., 2004; Storper and Venables, 2004), which means that belonging to the same cluster and therefore sharing the same (or similar) values, culture and communication codes enhances knowledge circulation (see later for more discussion on this point).

For modelling the knowledge barter between agents *i* and *j*, we adopt Cowan and Jonard's rule (2004). Defining *m* as the number of knowledge categories in which *i* can learn from bartering (i.e. $V_{i,k}^{B}(t+1) > V_{i,k}(t)$) and *n* as the corresponding number for *j*, the barter between *i* and *j* occurs in a number of categories equal to min *(n,m)*.[1]

Eventually, after the two randomly selected agents have exchanged knowledge, the economy moves to the next period and all the previous steps are repeated.

The rule of knowledge barter deserves some further consideration. First of all, the distinction between experts and non-experts implies that in the model there are: a) actors (i.e. the experts), who are *sources* of knowledge and can play either the role of *gatekeepers* or *external stars*; and b) other actors (i.e. the non-experts), who are *net absorbers* of knowledge. This distinction between sources and net absorbers of knowledge is possible because the rule of knowledge exchange does not require that the amount of knowledge acquired by each agent is exactly the same, or even similar. We

[1] If an agent can learn in more categories, the categories in which learning takes place are chosen randomly with uniform probability.

only assume that each agent is able to recognize whether another agent knows more or less than himself in a given field. As a consequence, knowledge exchange between experts and non-experts tends to result in asymmetric learning, since experts (when provided with knowledge in the category in which they are specialized) learn less than non-experts do.

Second, we assume that both types of agent learn in the same number of categories, capturing in a static way (i.e. within each period) the idea of dynamic reciprocity, which can be found in the empirical literature on know-how trading (von Hippel, 1987). This suggests that a balance of knowledge and information given and received is obtained over a sufficient time horizon.[2]

Finally, the assumption that in each period only a pair of agents can exchange knowledge has an obvious but important implication that at one time, each agent can interact with *at most* one other agent. This captures the idea that social interactions are costly both in terms of time and resources and it has two important implications. First, for the sake of model simplification knowledge diffusion takes place only as the outcome of direct and purposeful exchanges between actors. This implies that, in the model, knowledge exchange does not *explicitly* encompass the idea of local buzz, defined as the possibility of taking advantage from local information, inspiration and news by just being there, without any specific investment (Bathelt et al., 2004). Nevertheless, in the model this important notion, as emphasized in the literature, is captured by variations in the parameter α_W (as discussed above). This parameter catches all those factors that affect the ease of knowledge flows between agents and therefore in the model, the relevance of local buzz, implying a greater diffusion of knowledge within the cluster, is measured by an increase in α_W.

The second implication of the previous assumption is that denser networks are not necessarily socially beneficial. To explain this point we propose the following mental experiment. Suppose that knowledge exchange between two agents, say *i* and *j*, takes place just before another link, involving one of the two agents (say *i*) and a third agent (say *y*), is drawn. On the basis of the mechanism introduced in our model, the knowledge barter between *i* and *j* may eliminate the incentives for *i* to exchange

[2] Implicitly, it is assumed that the access to knowledge has a value in itself and therefore knowledge is not considered as an input of an innovation process through recombination.

knowledge with *y*, that is, the link between *i* and *j* may substitute (in use) the link between *i* and *y*. In the rest of the paper, we will refer to this effect as *substitution effect*. Such an effect can have relevant social consequences, because in general, links are heterogeneous in the level of the overall knowledge that can be exchanged through them. To explain this point, let us suppose that the link between *i* and *j* substitutes the link between *i* and *y*, but the level of overall knowledge exchanges is larger for the latter than for the former (this may happen if *y* could learn a lot by bartering knowledge with *i*). In this case, if the link between *i* and *j* is added to an existing network that includes the link between *i* and *y*, then adding this new link will actually decrease the level of knowledge of the cluster as a whole. In Section 4, our results concerning the impact of global pipelines on the cluster performance emphasize the importance of the substitution effect, which regards both links among experts as well as links between experts and non-experts.

3.1.3 Aggregate knowledge and cluster performance

The average level of knowledge in each cluster measures the overall cluster performance. Given that agent *i*'s average knowledge level is:

$$\overline{V}_i(t) = \frac{\sum_{k=1}^{K} V_{i,k}(t)}{K} \tag{2}$$

then the average level of knowledge in the economic system is:

$$\mu^t = \frac{\sum_{i=1}^{N} \overline{V}_i(t)}{N} \quad (3).$$

Therefore, for each cluster the average level of knowledge is:

$$\mu_r^t = \frac{\sum_{i \in N_r} \overline{V}_i(t)}{n_r} \tag{4}$$

3.2 The experimental design

In all the simulation exercises, there are 500 agents (30 of them being experts) and 5 knowledge categories.[3] All the other parameters are allowed to change and in order to

[3] These are the same values as in Cowan and Jonard (2004).

explore the parameter space of interest, which is of a high dimension, we proceed as follows. First of all, we implement a random sampling procedure as described in detail below for assigning the values to each parameter. Second, we record the aggregate knowledge levels *in the long run* for each drawn combination of the parameters. Finally, we run linear regressions to study the effect of each parameter on the aggregate knowledge.[4]

As concerns the random sampling procedure, in each run the values for p_{EEW}, p_{ENEW}, p_{NENEW} and α_W are (independently) drawn in the interval [0; 1] with uniform probability. Given p_{EEW}, p_{ENEW}, p_{NENEW} and α_W, the values for p_{EEB}, p_{ENEB}, p_{NENEB} and α_B are (independently) drawn in the intervals [0; p_{EEW}], [0 p_{ENEW}], [0; p_{NENEW}] and [0; α_W], respectively.

With regard to cluster size, we consider two cases: a) the clusters are symmetric when both have 250 agents each; b) the clusters are asymmetric when Cluster 1 has 400 agents and Cluster 2 has 100 agents. Then, taking into account knowledge endowment, there are also two cases: a) a symmetric case with 15 experts in each cluster (i.e. three experts in each knowledge category) and b) an asymmetric case, in which Cluster 1 has 25 experts (i.e. five in each category) and Cluster 2 has 5 experts (i.e. one in each category). Given the size and the knowledge endowment of the clusters, there are four possible scenarios (Table 1). In each run, the scenario is attributed through a uniform distribution.

The experimental design can be summarized as follows.

Step 1: The values for the parameter vectors p and α and the scenarios (A, B, C and D) are randomly assigned;

Step 2: The system runs for 100,000 periods, which is a sufficiently long period to observe convergence in the average knowledge level, and μ^{100000}, μ_1^{100000} and μ_2^{100000} are recorded;

Step 3: Steps 1 and 2 are repeated 200 times;

Step 4: OLS regressions are estimated using μ^{100000}, μ_1^{100000} and μ_2^{100000} as dependent variables.

[4] For a discussion of merits and limits of regression analysis in simulation experiments see Kleijnen (2008)

The explanatory variables are p, α , some interaction variables and the dummy variables SCENARIOB, SCENARIOC and SCENARIOD (with Scenario A used as the reference and the vector of the three dummies labelled as *S*). In particular, Section 4 presents three models, respectively Model 1, Model 2 and Model 3:[5]

$$\mu^{100000} = \beta_0 + \beta p + \lambda\alpha + \theta p_{EEB}\alpha_W + \gamma S + \varepsilon \tag{5}$$

$$\mu_1^{100000} = \beta_0 + \beta p + \lambda\alpha + \theta p_{EEB}\alpha_B + \varepsilon \tag{6}$$

$$\mu_2^{100000} = \beta_0 + \beta p + \lambda\alpha + \theta p_{EEB}\alpha_B + \varepsilon \tag{7}$$

with $\beta \equiv [\beta_{EEW}\ \beta_{EEB}\ \beta_{ENEW}\ \beta_{ENEB}\ \beta_{NENEW}\ \beta_{NENEB}\ ]$ and $\lambda \equiv [\lambda_W\ \lambda_B]$.

Table 1 – The four scenarios

Size/N°Experts	**Symmetry**	**Asymmetry**
Symmetry	**Scenario A** Size: 250-250 N°Exp: 15-15	**Scenario C** Size: 250-250 N°Exp: 25-5
Asymmetry	**Scenario B** Size: 400-100 N°Exp: 15-15	**Scenario D** Size: 400-100 N°Exp: 25-5

Model 1 considers the whole set of runs (200), estimating the performance of the overall economy by controlling for the different scenarios by means of the three dummy variables. Model 2 and Model 3 focus on specific scenarios, estimating the performance of one specific cluster under different conditions in terms of size and knowledge endowment of the clusters. In Model 2 we consider the runs under Scenario D, which is

[5] By construction, $p_{EEB} * \alpha_W$ and $p_{EEB} * \alpha_B$ are highly correlated, which creates a problem for both variables being in the same regression. For this reason, we considered three variants for each model, including each interaction in turn, and the two simultaneously (all the regressions are available upon request). In each model, the formulation chosen is the one for which i) the variable included is statistically significant when included in isolation; ii) the magnitude of the coefficient for the included variable varies less than the coefficient of the excluded variable when the other variable is added; iii) the adjusted R^2 is the largest.

characterized by asymmetry both in terms of size and knowledge endowment, with as dependent variable the average knowledge of Cluster 2, a small cluster (i.e. 100 agents) with a relatively small knowledge endowment (i.e. 5 experts). Model 3 considers instead the runs under Scenario B, which is characterized by asymmetry in terms of size, again with the average knowledge of Cluster 2 as dependent variable, which has only 100 agents, among which there are 25 experts, being therefore a small cluster with a relatively large knowledge endowment.

In the three models, we focus on the impact of the experts' external connections (i.e. global pipelines) on cluster performance; these are given by $\frac{\partial \mu^{100000}}{\partial p_{EEB}}$, $\frac{\partial \mu_1^{100000}}{\partial p_{EEB}}$, and $\frac{\partial \mu_2^{100000}}{\partial p_{EEB}}$. A positive sign of the derivative implies a role as knowledge gatekeepers for the experts, because an increase of their external connections with other experts outside the cluster benefits the cluster itself, in terms of average knowledge. Instead, a negative sign is associated with a role as external stars for experts. Moreover, the direct effect as measured by β_{EEB}, θ also provides information about the role of experts, *mediated* by those factors affecting the ease of knowledge diffusion, as measured by α.

4. Simulation findings

The presentation and discussion of results is organized into three parts. First of all, we comment on the findings concerning external relations in answer to our main research question. Second, we briefly comment on the results for the other variables in the regressions. Finally, we provide a qualitative discussion on the robustness of the results when some of our simplifying assumptions are removed, with particular attention to the assumptions about competition and absorptive capacity.

4.1 When do global pipelines enhance knowledge diffusion in clusters?

In this section we comment on the findings concerning global pipelines, that is the effect of variations of $p_{EEB}, p_{ENEB}, p_{NENEB}$ on the average knowledge diffusion. Table 2 reports estimates for the economy as a whole (Model 1) and for Cluster 2, with two different definitions: a small cluster with few experts (Model 2) and a small, highly knowledgeable cluster (i.e. with many experts) (Model 3). In line with theoretical and empirical arguments in the existing literature, our model shows that global pipelines (experts' external connections) play an important role in knowledge diffusion, adding some interesting new insights on conditions when they contribute to increasing the average knowledge of clusters.

Table 2 – The OLS estimations

	Model 1	Model 2 (Scenario D)	Model 3 (Scenario B)
P_{EEW}	-0.4884673*** (0.1540349)	-0.7103125 (0.5420813)	0.1711639 (0.5285919)
P_{ENEW}	0.0239632 (0.1546942)	0.1288492 (0.4114356)	0.0263962 (0.8581236)
P_{NENEW}	0.6541183*** (0.1411159)	0.9416772 ** (0.4575994)	0.5856686 (0.5162222)
P_{EEB}	-0.8420038** (0.3074168)	0.2759742 (0.7197708)	0.8761704 (1.045618)
P_{ENEB}	-0.1419344 (0.1958502)	-0.9669713 (0.5382138)	-0.8367116 (0.8043855)
P_{NENEB}	-0.5735592*** (0.1854408)	-3.918405*** (0.7580444)	-3.053541*** (0.6145664)
α_W	7.141501*** (0.1985596)	6.662774*** (0.4318161)	5.43931*** (0.5512942)
α_B	0.826315*** (0.2057179)	0.7698622 (0.7547065)	2.710159** (1.087334)
$P_{EEB}\ \alpha_W$	1.499561*** (0.5054079)		
$P_{EEB}\ \alpha_B$		3.313597* (1.592703)	-3.288531 (3.274625)
SCENARIO B	0.0260616 (0.0945728)		
SCENARIO C	-0.2302782** (0.029612)		
SCENARIO D	0.0446888 (0.0955961)		
Constant	1.803214*** (0.1602237)	1.606604*** (0.4496945)	2.765995*** (0.4558384)
N° obs.	200	52	46
Adj R^2	0.9644	0.9337	0.8542

Standard errors in parentheses.
Coefficients marked with ***, ** and * are significant at 0.01, 0.05 and 0.10 levels respectively.

The first important result is that when experts establish external connections with other experts the *direct* impact on local knowledge diffusion is negative and statistically significant (β_{EEB} in Model 1). In this case, a *substitution effect* is at work: if one expert within the cluster exchanges knowledge with an external expert, his incentive to share knowledge with local partners (especially with non-experts) diminishes. This finding is in line with some recent empirical evidence (Giuliani and Bell, 2005; Morrison and Rabellotti, 2009), pointing to a detrimental effect of experts' global pipelines for knowledge diffusion within clusters. Therefore, as a 'natural tendency' (i.e. as measured by direct effect), actors in global pipelines act as *external stars* rather than *knowledge gatekeepers*: when opportunities for external connections emerge, they engage themselves with external actors, ignoring local ones and hence potentially hindering the cluster's knowledge accumulation.

Second, the impact of global pipelines is significantly augmented by the presence of high quality buzz. This is illustrated by the coefficient of the interaction variable $p_{EEB}\alpha_W$, which is positive and statistically significant. In Model 1, the marginal effect of $p_{EEB} = -0.84 + 1.5\alpha_W$ suggests that the role of experts' global pipelines depends on how easily knowledge circulates once it has reached the cluster. For large values of α_W, externally connected experts act as knowledge gatekeepers, whereas for small values, when knowledge circulates laboriously within the cluster, experts perform the role of external stars. In other words, on the basis of the interpretation of α_W as indirectly capturing the presence of a local buzz (Section 3.1.2), externally connected experts act as knowledge gatekeepers in the presence of a high quality local buzz and as external stars otherwise. An explanation of this result is as follows. Notwithstanding the above-described experts' natural tendency to behave as external stars, large values of α_W (high quality buzz) facilitate the circulation of experts' knowledge within the cluster, therefore offsetting their low propensity to exchange knowledge locally. This finding confirms that, as stressed by Bathelt et al. (2004), the local buzz is helpful for making external knowledge comprehensible and accessible to other local actors; in other words it reduces the trade-off between too much inward-looking and too much outward-looking cluster structures.

Third, the extent to which global pipelines affect local knowledge diffusion also depends on the characteristics of the cluster (i.e. size and knowledge endowment). Indeed, we observe in both Models 2 and 3, in which the dependent variable is the average knowledge level in Cluster 2, that the coefficient of p_{EEB} is positive, but insignificant, rather than negative (as in Model 1). Similarly, differences emerge also by comparing the outcomes of the interaction terms ($p_{EEB}\alpha_W$; $p_{EEB}\alpha_B$) under the three different model specifications. In particular, in Model 2 when the cluster is small both in terms of number of agents and knowledge endowment (Scenario D), there are by construction few experts, with a low likelihood of establishing external connections and therefore global pipelines play a marginal role. However, their impact changes and becomes positive and significant when the interaction term $p_{EEB}\alpha_B$ is considered. In this case, the few experts' global pipelines matter because, besides providing access to otherwise unavailable knowledge, their effect is amplified by the ease of knowledge transmission across clusters (large value of α_B). In Model 3 (Scenario B), the cluster is small in terms of size but large in terms of knowledge endowment and therefore there are many opportunities for profitable exchanges *within* the cluster. In this case, the interaction term $p_{EEB}\alpha_B$ is negative and insignificant, suggesting that the combination of global pipelines and ease of knowledge exchange *between* clusters is of limited importance when the local knowledge endowment is large. Indeed, if the number of local experts is high, there are always several paths connecting non-experts to valuable knowledge they do not possess.

Besides experts' external linkages, the model also provides interesting results on other types of external relations. In particular, concerning external relations involving non-experts between the clusters (p_{NENEB}), in all the three models their coefficient is negative and statistically significant. The negative sign is due to the substitution effect: the use of external links (among non-experts) implies by assumption the diffusion of a smaller fraction of knowledge, instead of the use of a link within the cluster.[6]

4.2 Intra-cluster linkages and local buzz

Table 2 provides some further insights about the impact of intra-cluster linkages on knowledge diffusion, which complement the findings on global pipelines presented in the previous section. Broadly speaking, our findings confirm the importance of local embeddedness for local knowledge diffusion. In particular, the coefficient of p_{NENEW} is

[6] The coefficient of p_{NENEB} is larger in both Models 2 and 3 than in Model 1 because in the two former models, the dependent variable is the average knowledge of a single cluster (Cluster 2). Therefore, when knowledge is exchanged between agents belonging to different clusters, the increase in the knowledge of the agent outside the cluster does not impact on the dependent variable. Clearly, such an effect is not present in Model 1, where the dependent variable is the average knowledge of the whole economy.

positive and significant in Models 1 and 2 and from that we may conclude that intra-cluster relations between non-experts boost knowledge diffusion. This is a confirmation of the role played by social relations, in particular among less knowledgeable actors, as an important source of learning.

With regard to the relation among experts, findings are instead less clear-cut because p_{EEW} is statistically significant (with a negative sign) in Model 1 but it is not in Models 2 and 3. To explain this result we can again refer to the substitution effect: more connections among experts within the cluster imply a less intense use of links with non-experts and this is detrimental to knowledge diffusion, since it reduces the learning opportunities for non-experts.

Finally, the variable α_W measuring the ease of knowledge diffusion within the cluster can be interpreted as a proxy for the role of local buzz on knowledge diffusion. In other words, this variable captures the effect generated by the presence of a cohesive socio-economic community, sharing a common history, cultural traditions and habits. As seen in Section 2, the literature has widely emphasized that a thick institutional environment enhances mutual understanding and trust, facilitating communication among cluster members (Gertler, 1995; Storper and Venables, 2004). Along these lines, in all models α_W is always positive and significant with a particularly high value, therefore confirming that local buzz matters for knowledge diffusion.

4.3 Model robustness: relaxing assumptions about competition and absorptive capacity

In our model there are two important assumptions about competition and absorptive capacity that need to be addressed in order to understand how our findings, in particular those concerning global pipelines, may change if they are relaxed.

First of all, the model ignores the role of competition while it is obvious that in the real world competitive relations matter in clusters. With regard to informal knowledge exchange, it can be argued that if knowledge represents a competitive advantage, the incentive to barter knowledge among competing firms is low (Cassi and Zirulia, 2008). Having said that, in order to understand the social consequences of competition in our model, we need to examine which are the competing firms. If competition mainly involves firms (experts and non-experts) within the same cluster, we might expect a reduction of the internal circulation of knowledge and consequently an increase of the likelihood of knowledge exchanges with agents outside the cluster. With regard to experts, competition is therefore an incentive to behave as external stars. On the contrary, if competition occurs mainly between experts in different clusters, their propensity to barter externally is reduced, thus increasing their likelihood of exchanging knowledge with other agents within the cluster. This would make experts more likely to act as knowledge gatekeepers, i.e. more prone to diffuse internally the knowledge they acquire outside the cluster (although the lower incentives to barter with external experts may reduce the pool of knowledge to which they have access).

Second, in our model we have not taken into account the role of absorptive capacity (Cohen and Levinthal, 1990). Indeed, in the model the fraction of knowledge that any agent can learn from a more knowledgeable partner does not depend on his initial level of knowledge. In other words, there is no need for some pre-existing knowledge in a specific category in order to absorb new knowledge. To account for the role of absorptive capacity, it can be assumed that knowledge exchange requires agents to be fairly similar in their initial level of knowledge in each specific category. By imposing this assumption, we limit the possibility for experts to exchange knowledge with non-experts, hence reinforcing, *ceteris paribus*, the emergence of external stars.

5. Conclusions

The recognition of the importance of both external and internal linkages in successful clusters has generated a recent stream of empirical studies investigating the characteristics of knowledge gatekeepers, defined as actors that serve two functions: external knowledge sourcing and diffusion within the local system (Giuliani and Bell, 2005; Morrison, 2008; Graf, 2011). This paper contributes to this literature with a formal model that investigates when global pipelines do actually contribute to increase local knowledge.

Overall, we show that under different model settings the impact of global pipelines changes significantly. This result is an original contribution to the literature, which has mostly overlooked the investigation of the conditions under which external links can affect cluster learning dynamics. In our simulation model, actors, who are experts (i.e. more knowledgeable than the average actors in the cluster) and externally connected, spontaneously behave as *external stars* rather than *knowledge gatekeepers*. Therefore, the existence of global pipelines is not *per se* a guarantee for better cluster performance in terms of knowledge acquisition. A condition for global pipelines to behave as knowledge gatekeepers is the existence of a high quality local buzz, i.e. when external knowledge reaches the cluster it is important that its diffusion mechanisms function very efficiently. In other words, our findings show that successful clusters need a good mix of internal density and external linkages. Moreover, our model underlines that global pipelines are particularly important when the cluster is small and weakly endowed in terms of knowledge base, because in this case, access to knowledge coming from outside is key to improving the cluster performance.

In terms of policy implications, our findings underline the complexity of the development of initiatives aimed at supporting spatial clusters. During the last decade, in many parts of the world international organizations, national and local institutions have promoted a large variety of policy initiatives aimed at establishing and enhancing mechanisms for interactive learning within clusters (Ceglie and Stancher, 2009; Landabaso and Rosenberg, 2009). More recently, the attention of policy makers has also been drawn to the necessity to favour the development of global pipelines in order to avoid cluster lock-in (Pietrobelli and Rabellotti, 2007). As a whole, we can conclude that both external and internal interactions contribute to increasing cluster knowledge; nevertheless, the still unresolved issue is how to generate an effective mix.

This paper shows that sustaining the development of global pipelines through institutional and infrastructural support as well as through the attraction to the cluster of globally connected actors is especially important when clusters are small and dominated by non-experts. Nevertheless, it is also important to counteract the natural tendency of actors within global pipelines to behave as external stars. This requires a high quality local buzz, which is often the spontaneous result of spatial proximity but it cannot be taken for granted. It can also be the case that incentives are needed to convince globally connected actors to play the role of knowledge gatekeepers.

These conclusions leave open some issues for further research. One question to address concerns the incentive scheme, which may be needed for turning a natural external star into a gatekeeper. As already mentioned, a second issue is how policy makers can be supported in their search for the right mix of internal cohesiveness and outward orientation.

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