The Effect of Co-Inventorship Networks on Regional Innovativeness

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Abstract

These days are characterised by intensified globalisation, rapid technological change and the appreciation of nonmaterial resources. Production of knowledge and information and the ability to adapt them play an important role in these processes and knowledge production, knowledge diffusion and innovation becomes more and more important in regional competitiveness. In recent years economic development policies evolved around the concept of cluster-based development. Parallel to this process economic geography and networks became two important and mutually dependent research areas in the economic and innovation literature. Theories of economic growth had placed the role of knowledge into the focus which led to the analysis of knowledge diffusion and knowledge networks as well as locality in economic growth.
In this study we try to reveal the links between the structural characteristics of knowledge networks and regional innovativeness. In order to do this, we make use of an extense database, built in the recent years, which contains data on co-inventorship networks in the high-tech industry. The database covers three European countries (Germany, France and the United Kingdom) and more than 25 years. This database allows us to construct knowledge networks among NUTS-2 level regions of these countries, then the structural characteristics of these networks are used to explain innovative activity in the regions.
Our results show that the underlying structure of knowledge networks indeed contributes to innovativeness, moreover, a special, integrated measure of 'network quality' developed in this paper has additional explanatory power in some cases. We also find a modest role for diversity in innovativeness.

Keywords: academic knowledge transfers; network analysis; technological change; economic growth; regional development

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1. Introduction

Networks of researchers and inventors play an important role in reaching economic and social achievements. Not only do they strengthen scientific activity but contribute innovation and in turn technological development. On the other hand they determine the intensity and quality of knowledge transfers between the academic and industrial sector and affect the competitiveness of regions depending on the structure of these networks. The same amount of expenditure on research and development can lead to different effects in innovative activity in different regions and several factors can be attributed to this difference. Among factors like local infrastructure, entrepreneurship, cultural factors the role of research and inventor networks are also important.

It should not be the overestimation of the role of innovation if we interpret it as the main driving force behind economic – and in certain respect social – development. The development and application of new procedures contributes to extraordinary possibilities to obtain economic profits at the micro level and leads to a more efficient allocation of resources at the macro level which, in certain cases, improves social welfare as well. Developments in the literature on endogenous growth theory provide a solid basis for these arguments (Romer, 1986, 1990).

On the other hand, individual innovations at the micro level may diffuse and contribute the macro level efficiency mentioned above. The nature of this diffusion therefore comes as another important question. The diffusion of knowledge has several important characteristics along the dimensions of time and space and these characteristics deeply affect not only the possibilities of companies and regions but the distribution of social benefits stemming from new developments. Regarding the spatial aspects, the widely expanding literature on new economic geography, initiated by Krugman (1991) can be cited. The practical relevance of both spatial and dynamic issues are covered by the literature on knowledge spillovers which test empirical the existence and nature of knowledge diffusion processes (see for instance Jaffe, 1986, 1989, or Jaffe et al., 1992). A further important area of interest in this respect is to reveal the factors which determine the extent to which academic knowledge is converted into useful industrial applications. For this issue see the reviews of Varga (2004) and Goldstein (2008).

Breschi and Lissoni (2007) emphasize that knowledge, capable to generate innovation, diffuse mainly through local social networks. The development of these networks, in turn, depend on several cultural factors as pointed out by Saxenian (1994), Fischer et al. (2001) or Feldman and Desrochers (2004) among others.

As it is clear from those mentioned above, both the generation and diffusion of economic knowledge requires some kind of network. So, it is straightforward to tackle these issues within the new paradigm of network theory which naturally leads to the thematization of research questions in the context of network. This is also confirmed by the fact that the economic literature reports important findings in the field of theoretical and empirical research on networks.

The literature, focusing on the role of networks in innovation diffusion, is still at the beginning of a long research agenda. In spite of much work which emphasizes the role of these relationships in the intensity and quality of knowledge transfers from academia to the industry (see for example Franzoni and Lissoni (2007)), there are still little efforts in empirically testing the contributing effects. However, a favorable line for further research is the Social Network Analysis which offers a more sophisticated way for analysis (Coulon, 2005, Ozman, 2006). Several recently published studies indicate the interest towards the SNA techniques for research in the field of knowledge spillovers from the academic sector (Maggioni, Nosvelli and Uberti, 2006, Ponds, Oort and Frenken, 2007). On the other hand only a few studies examine the role of network structure and network quality in these fields although it is well known that the quality of the realization of some function or effect is highly dependent on the structure of the system in which this function or effect is embedded.

Disregarding the question of structural issues is annoying also from the viewpoint that differences in the configuration of network relationships can generate important discrepancies along the path of technological development. The studies of Valente (1995), Cowan and Jonard (1999) and Spencer (2003) attribute important role for the structure of networks in this consideration. On the other hand, Ouimet, Landry and Amara (2004), Morrison and Rabellotti (2005) and Giuliani (2007) emphasize the rol of the position in a given network. According to Giuliani (2004) network density, the strength of network ties and openness are all important factors of innovation whereas findings of Ahuja (2002) suggest that the so called structural holes – to be defined later – act against innovativeness.

Varga and Parag (2009) analyze the effect of international publication networks on university patenting. According to their results the quality of these international publication networks affects academic knowledge transfer. As a conclusion for economic policy they point that not only R&D subsidies can be used as measures of strengthening knowledge based economic development but the reasonable support in developing academic research networks.

According to those summarized above it is clear that the diffusion of economically useful knowledge can result in considerable economic growth as testified by high-tech agglomerations (e.g. the Silicon Valley) all around the world. On the other hand, it is also clear that research or inventor networks are an important factor contributing to this economic success as they are the primary mediators of knowledge diffusion. Structural characteristics such as the intensity of relationships, concentrity of links and centrality are important as they affect the way knowledge flows among the members of the networks thus the way and time span how knowledge flows from one place to another both in the network and in space. Therefore, the structure and other characteristics of these networks are supposed to be an important determinant of economic growth not only at the macro level, but on the regional level also.

In this study we try to measure the effect of the quality of network position to the innovative potential of network members. By network quality we mean a special combination of different structural characteristics to be defined later. Our study, on the other hand, uses a special dimension of analysis, namely European NUTS2 regions. That is, we build co-inventorship networks among 97 regions based on patent co-inventorship data and examine the effects of structural characteristics on the innovative potential of these regions, namely patenting activity. Our primary goal in this respect is to show that network quality based on several structural characteristics provides an additional explaining factor in determining innovativeness of a region. That is, the extent of innovativeness of a region is affected by the underlying knowledge network in which the region operates its economic activity. Due to availability of data our analysis is restricted to the high tech sector (as defined by classification of the European Patent Office) and to 3 countries, namely Germany, Franc and the United Kingdom.

The paper is structured as follows. In the next section we present the database used for our analysis, then the third section describes the network measures used. The empirical models and their results are presented in Section 4 while Section 5 gives a brief summary and concludes our analysis.

2. The database

We use two different databases in our study. First, we use the database of the European Patent Office (EPO) in order to build up the co-inventorship networks, second, the database of the Eurostat is used to obtain data on regional R&D expenditures. The patent data of the EPO contain information about the address of the inventors and obviously the sector to which the given patent belongs. We took this data from 1978 to 2005 and from this information we extracted co-inventorships in the case of each patent and built up the network of patent inventors. In the next step this network was aggregated into European NUTS2 regions. That is, we consider not network of individuals rather network of regions, but maintaining that behind this network lies the network of individuals. Further, the network among regions is a weighted one, meaning that an edge between two different regions has a weight referring to the number of patents on which inventors of the two regions had worked together.[1] Thus we have a network of regions in which the intensity of interregional relationships is reflected by the number of co-invented patents, nevertheless, the networks are constructed for every year in the period between 1978 and 2005.

The database covers the high-tech sector as used by the Eurostat methodology. In this classification the high-tech sector covers three subsectors as follows: (1) aviation; (2) computer and automated business equipment; (3) communication technology; (4) lasers; (5) micro-organisms and genetic engineering; (6) semi-conductors.[2]

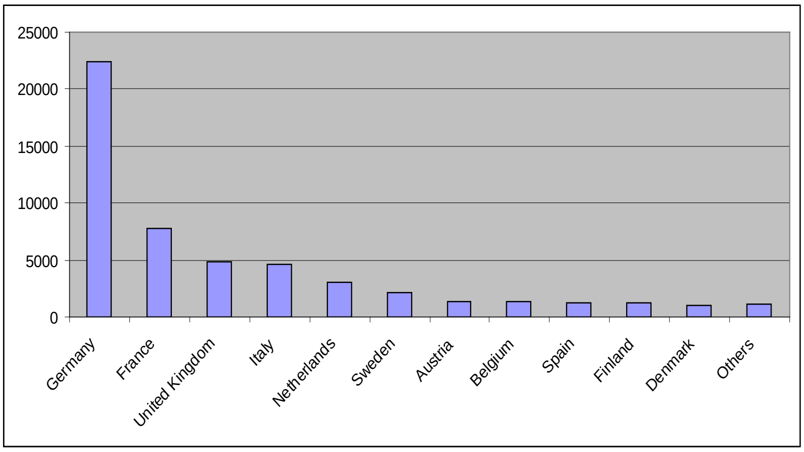

Figure 1. Total number of patent applications to EPO, 2005. (Source: Eurostat)

The database is being constructed for all European countries, however only part of the countries' statistics is already available thus we restricted our analysis to the three major countries active in the patent field. According to the patent statistics of the Eurostat, these

[1] Note that the weight of an edge between two regions refer not to the number of personal contacts but the number of co-invented patents between the two regions.

[2] The associated IPC codes are: (1) [B64B, B64C, B64D, B64F, B64G]; (2) [B41J, G06C, G06D, G06E, G06F, G06G, G06J, G06K, G06M, G06N, G06T, G11C]; (3) [H04B, H04H, H04J, H04K, H04L, H04M, H04N, H04Q, H04R, H04S]; (4) [H01S]; (5) [C12M, C12N, C12P, C12Q]; (6) [H01L].

countries are Germany, France and the United Kingdom, with reference to the total number of patent applications to the EPO. (See Figure1.)[3]

Looking at the networks given in each year we find that these networks are quite sparse and very instable in the sense that most links dissolve and new ones form year after year. Table1 contains stability measures for the different sectors, as counted by the average share of stable links in total links. In the 1 year data this stability is about 5-10% which refers to very 'hectic' network evolution.

	1 year	4 years
Aviation	4,88%	76,47%
Computer	8,55%	74,56%
Communication	9,83%	74,59%
Laser	5,81%	77,52%
Semiconductor	9,02%	73,99%
Micro-genetic	7,30%	76,17%
Hightech	12,21%	75,15%

Table 1. Stability of networks in 1 year and 4 year aggregation

In order to avoid this low stability and to account for the fact that a co-inventorship in a given year for a patent application probably covers cooperation among inventors longer than one year, we aggregated data through 4-years windows. This means that the links considered for a given year not only contains the patent applications for that specific year but applications made in the 3 consecutive years as well. This method was rolled over the years thus we have 25 years in our database (28 years originally, and 3 years lost from the end because of this aggregating method), in each year containing a much dense and much stable network. (See the second column of Table1). This aggregation method is supported by the assumption that a co-inventorship recorded in a given year by patent statistics is not reduced to just one year. Considering that work on a patent application requires several years to be completed, this assumption seems reasonable. In our specific case, we use the supposition that a patent application in a given year means cooperation among the inventors in that specific and 3 previous years.

A final problem with the patent statistics is that information is not fully processed in the recent years therefore we can not use data from 2000 to 2005 as these are biased according to

[3] Although Figure1 refers to 2005 data, the available time series show that the three leading countries are invariant during the period 1995-2005.

the unprocessed applications. This naturally limits the scope of our analysis, but the bottleneck is rather data on R&D than on networks.

Regarding data for regional R&D expenditures, Eurostat publishes these data only for the years 1995, 1997 and 1999. This restricts our analysis to these three years and we can not truly exploit the longitudinal dimension of our network database. The other difficulty is that there is no available data on R&D expenditures in the high-tech sector on the regional level. There would be a possibility to adjust overall R&D according to the share of the high-tech sector in regional GDP. This solution, on the other hand, is quite ad-hoc. Instead, we use total R&D at the regional level and carry out our analysis on both high-tech patents and total patents, that is, we try to trace the effect of high-tech co-inventorship networks on both high-tech and overall patenting whereas we control for overall R&D expenditures regardless of the sector in consideration.

Finally, a further problem emerges regarding the regional R&D data in the UK. In our database only NUTS1 level data are presented in the UK, therefore we had to aggregate our network data to the NUTS1 level as well – this method does not mean any methodological problems, the nodes of the networks are simply NUTS1 regions instead of NUTS2 regions. However, in the other two countries, we maintained the NUTS2 division as R&D data is available at that level for these countries.

To sum up all those mentioned according to our dataset, we have data for three years, 1995, 1997 and 1999 for regional R&D expenditures at the NUTS2 level for Germany and France and at the NUTS1 level for the UK. For all these years we also have a network of these regions based on high-tech patent co-inventorship, from which we develop a network quality measure do be described in the next section. As our dependent variable, we also have a record of high-tech and total patent number in the given regions and in the given years.

3. Network measures

As it was outlined in the Introduction, the aim of this paper is to trace a link between structural characteristics of knowledge networks and regional innovativeness. In the previous section we presented the way we measure knowledge networks through co-inventorship networks. However, how to measure structural characteristics in networks remains to be explained. Our aim in this paper, following Varga and Parag (2009), is to introduce a special network quality measure which combines different aspects of network structure into one single measure. We use three different measures in order to capture the characteristics of the position of different regions in the co-inventorship network. These measures take into account the direct environment of a given region in the network space thus approximating the potential knowledge flows to that given region. We introduce these three measures in what follows. The three measures are based on the methodology developed by Varga and Parag (2009) but they are adjusted to the present setting as the underlying network is different.

Size

The first measure refers to the size of a given node with respect to the number of its links. Basically, this is the usual 'degree' measure in social network analysis. We use the notion 'size' to denote this characteristic in order to emphasize that this measure are used in our context to capture the weight of a given region in the co-inventorship network. To calculate the size, we simply counted the number of links each region has with other regions. We use an unweighted measure of link number, i.e. we considered only whether there exists cooperation between two regions but we disregarded the intensity of this cooperation. Then we normalized this number with the highest size in the network.[4] Thus we have a measure of the (network-related) size of a given region which ranges between zero and one with value zero if the region has no links and value one if it has the most links in a given year.

Let us denote the (unweighted) adjacency matrix of the network by A. The general element of this matrix is a_{ij} which gives the existence of cooperation between region i and j. That is, $a_{ij} = 0$ if the two regions do not cooperate and $a_{ij} = 1$ if they cooperate. Using this notation, our size measure can be written in the following way:

$$S_i = \frac{d_i}{\max_j (d_j)}$$

where N is the number of regions in our network and d_i is the number of links of region i defined as:

$$d_i = \sum_{j=1}^{N} a_{ij}$$

[4] This normalization was carried out on a yearly base, i.e. the maximal size was determined for each year and all other sizes in a given year were divided by the maximum of that year. This method controls for the change in overall link numbers and weights in the network which is present in the database.

Integrity

Our second measure is based on the idea that not only the link number of a given node can be important but its embeddedness into the whole network. We term this characteristic as the 'integrity' of a node as referring to the extent to which a given node is integrated (embedded) into the network. Our integrity measure captures the intensity of cooperation between partners thus in the case of this measure we exploit information in the weights of our network data. First we calculate the average intensity of cooperation between a given node and its partners, i.e. we divide the sum of cooperation (the weights of links) by the number of links a region has. Then for each region we take the average of this cooperation intensity among the given region's partners. Finally, as in the case of size, we normalize the integrity measure by the maximum value of this integrity in a given year.

Let us denote the weighted adjacency matrix by W . Then the general element of this matrix is w_{ij} which gives the intensity of cooperation between region i and region j. The only restriction for w_{ij} is to be nonnegative. Using this notation our integrity measure can be written in the following way. The cooperation intensity of a node j is:

$$L_i = \frac{\sum_{j=1}^{N} a_{ij} w_{ij}}{d_i}$$

Then the following expression gives the absolute integrity measure for region k :

$$K_k = \frac{\sum_{j=1}^{N} a_{kj} L_j}{d_k}$$

Finally, the normalized integrity measure is given by:

$$I_i = \frac{K_i}{\max_j (K_j)}$$

Concentrity

As our third characteristic of a given region in our co-inventorship network, we built a measure of concentrity. This measure is based on the observation that a more central position in the network gives better opportunities to exploit knowledge flows. In usual social network analysis there are several measures of centrality, but we developed a special measure to capture the immediate and 'one-link-ahead' structure of the network. That is, our measure reflects the extent to which a given region is central in the network with respect to the number of its links and that of its immediate neighbors. First we calculate the number of (unweighted) links per each node, then we average this over the neighbors of a given node. That is, concentrity measures that on average how many regions can be reached through one link. Using the notation introduced above, the absolute concentrtity measure can be written in the following form:

$$M_i = \frac{\sum_{k=1}^{N} a_{ik} \sum_{j=1}^{N} a_{kj} d_j}{\sum_{k=1}^{N} a_{ki}}$$

Then our usual normalization gives the final measure:

$$C_i = \frac{M_i}{\max_j (M_j)}$$

Network quality

Our goal is to show that the overall 'quality' of network position is an important factor in determining innovativeness. In order to capture this 'overall' dimension we combine our three measures introduced above. The basic intuition behind this step is that not only the size, the integrity or the concentrity of a given node determines its favorable or less favorable position in the network, but the combination of them (and possibly some more characteristics left out here). We term this combination as 'network quality' and we defined it as given below.

Let us consider three coordinate axes along which we measure the three characteristics defined above. These three values give a triangle in the space defined by the three axes. Our network quality is given simply as the area of this triangle. It is easy to show that the area of this triangle ranges between 0 and $\sqrt{3}/2$ and that its size increases as one of the measures increases. Figure 2 shows the basic idea behind the construction of our network quality measure.

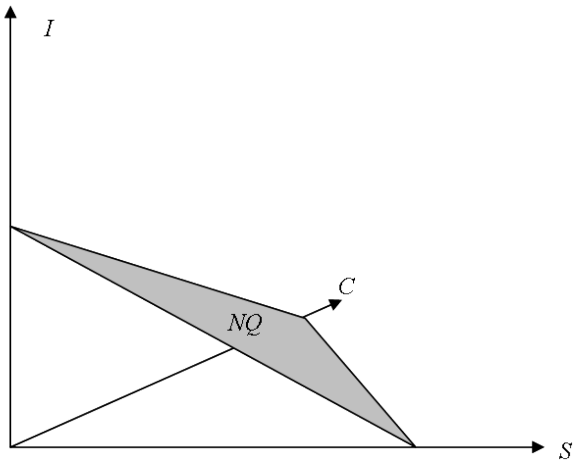

Figure 2. Graphical representation of our network quality measure

Using our previous notation, the following formula gives network quality (leaving the i index out):

$$NQ = \frac{\sqrt{\left(C^2 + I^2\right)\left(S^2 + C^2\right) - \frac{C^4}{C^2 + I^2}}}{2}$$

4. The empirical model and results

Our aim is to test whether network quality, defined as outlined above, have any effect on the patenting activity of European regions. In order to do this, we use the so called knowledge production function approach. This approach states that knowledge is produced with the use of specific production factors similarly to simple products or services, although these production factors are special. There are several attempts in the literature to determine factors of knowledge production. (For the original contribution see Griliches (1986) and Jaffe (1989)) The most common factors are related to research and development activities such as R&D expenditures, R&D personnel, or to human capital such as education. Other factors are also included in these models as possible additional explanatory variables in knowledge production. This line is followed in this study. We use R&D expenditures as the basic explanatory variable in our empirical models and then add network measures to see if they add something to the explanatory power of our model.

On the other hand, dependent variables raise some important questions in the knowledge production function approach. The basic problem is that the dependent variable should be knowledge itself but we can not directly measure knowledge. Different studies use therefore different proxies among which the most common ones are patents and TFP. In this paper we use patent number as the dependent variable, admitting that this solution has its own drawbacks.

Our knowledge production function to be used is based on those applied by Varga (2000, 2001) ans Acs and Varga (2005) which are a hierarchically structured version of that used by for example Jaffe (1989) and Griliches (1986). In constructing the regression models we followed the method used by Varga and Parag (2009). The basic model to be augmented later is simply as follows:

$$TOTPAT_i = \beta_0 \times (GERD_i)^{\beta_1} \times \xi_i$$

Where $TOTPAT_i$ is the total number of patents in region i regardless of the sector to which the patent belongs, $GERD_i$ refers to total R&D expenditures in region i, again, regardless of the sector. Taking logs of both sides we get the following equation to be estimated ($\varepsilon_i = \ln \xi_i$):

$$\ln TOTPAT_i = \beta_0 + \beta_1 \times \ln GERD_i + \varepsilon_i$$

In the next step, we suppose that the quality of network structure has an impact on the R&D productivity, that is, a better quality of the network structure in region i contributes to a more efficient R&D process. As a result, the same amount of R&D expenditure results in higher levels of knowledge production (patents). This hypothesis can be formulated as follows:

$$\beta_{1,i} = \alpha \times \ln X_i$$

where X_i is some measure of network quality. Substituting this equation to the previous one we get our final regression to be estimated:

$$\ln TOTPAT_i = \beta_0 + \alpha \times \ln X_i \times \ln GERD_i + \varepsilon_i$$

In what follows, we estimate five different models for the three years under consideration (1995, 1997 and 1999). The first model in each year is the baseline model where patent number ($TOTPAT$) is regressed on R&D expenditures ($GERD$) exclusively. In the following three models we augment the baseline model with our three structural network measures respectively: size, integrity and concentrity. That is, we place these measures in the place of X. The fifth model is also an augmented one but in this case we put our integrated network quality measure in place of X. The detailed results for all five models can be found in the Appendix as it would be overwhelming to present theme here. However, our main interest is if including any of the network measures in the analysis can improve the fit of the model, i.e. do network characteristics have any additional value in explaining patenting activity. We run ordinary least squares regression on the baseline and the augmented models and Table 2 presents the adjusted R^2 values for all 15 models (5 times 3) carried out the way outlined above.

Independent variable	**1995**	**1997**	**1999**
$\ln GERD$	0,251	0,636	0,529
$\ln S \times \ln GERD$	0,353	0,787	0,752
$\ln I \times \ln GERD$	0,311	0,687	0,690
$\ln C \times \ln GERD$	0,248	0,654	0,578
$\ln NQ \times \ln GERD$	0,399	0,777	0,773

Table 1. Explanatory powers of regression models with dependent variable *TOTPAT*.

The first observation from the table is that including any of our network measures in the regression characteristically improves model fit in all three years under considerations. Moreover, in 1995 and 1999 we have a significantly higher R^2 for the model in which network quality was used as a determinant of R&D efficiency. This suggests that the network structure in which researchers work has a determining force in patenting activity, or in our interpretation, knowledge production. On the other hand, our integrated measure of network quality seems to possess an additional value in explaining patenting activity, i.e. in 2 out of our 3 time periods this simple measure results in an improved model fit compared to individual structural characteristics. This points to the fact that we can not fully capture the role of network structure and position with one of these measures but a composite index of network quality does better in this respect. However, if we would like to pick one of our three structural measures as the most reliable proxy for network quality, it would be unambiguously network size, which has the highest contribution to the model fir in all years. Moreover, in 1995, using only size in the model gives better performance than using network quality. Recall, that size refers to the number of regions a given region has links with, regardless of the intensity of these relationships.[5] This suggests that the most sound effect can be attributed to the number of external links through which knowledge flows from different regions. In turn, one may conclude that it is rather the diversity of external knowledge sources what counts than the intensity of relationships from the same source of knowledge. Of course, this reasoning is based on the strong assumption that different regions have diverse knowledge bases, therefore links to different regions mean diversity of knowledge flowing into the region under consideration. This may be the case if regions are specialized in different industries but the contrary is true if regions are homogenous with regards to industries and knowledge bases. It is also interesting to note that the explanatory power of our models (irrespective of including only R&D expenditures or R&D and network measures also into the explanatory variables) significantly improves from 1995 to 1997 and 1999. As this improvement is present also in the baseline model we can not attribute this change to changes in the effect of network structure on R&D efficiency or even changes in the network data.

The analysis above was carried out for total patent number being the dependent variable. In what follows we see if the picture drawn above changes if only patents of the high-tech sector are used as dependent variables. Essentially the same methods were used as before, detailed results are presented in the Appendix, whereas Table 3 presents only the adjusted R^2 values of the models.

Independent variable	**1995**	**1997**	**1999**
$\ln GERD$	0,352	0,708	0,571
$\ln S \times \ln GERD$	0,483	0,845	0,791
$\ln I \times \ln GERD$	0,385	0,719	0,631
$\ln C \times \ln GERD$	0,349	0,713	0,593
$\ln NQ \times \ln GERD$	0,509	0,805	0,725

Table 3. Explanatory powers of regression models with dependent variable *HTPAT*.

[5] This means that size has the same value for example in two regions where the first have two partner regions from two patent co-inventorships and the second has also two partner regions with numeraous co-inventorships along both links.

The results now are somewhat changed. Again, including network measures into the explanatory variables improves the fit of the model. However, the role for our network quality measure is less sound. Now there is only one year, 1995 when network quality gives a better fit than simply network size and the difference of the two R^2 values is not that high. In the other two years network size gives better fit than network quality.

Comparing the results for total and high-tech patents gives interesting insights. Using the structure of high-tech patent co-inventorship networks as an additional explanatory variable in explaining patenting activity contributes to the model fit either if we try to explain high-tech and overall patenting activity. On the other hand, our integrated network quality measure seems to have and additional explanatory power compared to simple network size if we try to explain overall patenting and no such additional explanatory power can be detected if we try to explain only high-tech patenting. This result may come from the fact that as our network measures are built from patent databases, simple measures (size, integrity, concentrity) contain all useful information. On the other hand it is still interesting that even in the case of high-tech patents as dependent variable, network size seems to be the most important factor of network structure, that is, the number of partner regions is more important than the intensity of cooperation with these regions.

5. Summary and conclusions

Flows of economic useful knowledge inside regions and among them can result in significant economic growth as it is testified by traditional high-tech areas such as the Silicon Valley and newly evolving technological centers all around the world. It is also visible that research networks play more and more important role in obtaining economic and social achievements. They strengthen academic activity, contribute to innovation and technological change, and have important impacts on regional competitiveness. The same amounts of research and development expenditures can result in different impacts on innovation in different regions. These differences are caused not only by different levels of local infrastructure, entrepreneurship and cultural factors but also by the quality of research networks.

In this paper we tried to trace the role of the quality of research networks in innovative activity in European regions. For this end we used an extensive database on patent co-inventorship networks in the high tech industry of three European countries, Germany, France and the United Kingdom. Using structural characteristics of these co-inventorship networks we analyzed the effect of these characteristics on patenting activity as a proxy for innovativeness.

The results of our empirical analysis show that network characteristics indeed have an effect on patenting activity: including measures of network structures among the explanatory variables significantly improves the fit of our model. On the other hand, we constructed an integrated measure of network quality which reflects the characteristics of three different structural measures, namely size, integrity and concentrity. Our empirical results show that in some cases this integrated measure gives better fit than any of the individual structural measures. This additional explanatory power is present in the case when we explain overall patent number with R&D expenditures and network measures whereas no clear additional value is detected when the dependent variable is high-tech patent number.

A further interesting finding is that among structural measures simple network (or link-) size have the most significant effect on patenting which means that in addition to R&D expenditures, the number of partner regions have the highest effect on patenting. This is interesting as it shows that the intensity of cooperation between two regions is not that important as the number of such cooperations. Given some not too binding assumptions, this conclusion suggests a role for diversity in innovativeness as outlined by several previous studies.

Of course, our analysis has its natural limitations. First, due to availability of R&D data we could not exploit the longitudinal dimension of our network database which ranges from 1978 to 2000 and the analysis was restricted to three years (1995, 1997 and 1999) which are too close to each other to capture any dynamic characteristics in the relationships considered. Second, using only high-tech patents among the explanatory variables would be an important addition to the results. The nest step in the research project is to construct proxies for these data as long as they are not available. A further limitation which must be kept in mind when evaluating our results is that our network measures are built from patenting data therefore it reflects patenting activity which is our dependent variable. Although network measures are normalized and integrated, this problem results in a natural bias especially in the results obtained for high-tech patent numbers.

Finally, a natural extension of this study would be to include more countries into the analysis. Although the three countries analyzed in this paper gives the majority of patents in Europe and also they are the most central players in co-inventorship networks, leaving aside Italy, Spain or the Netherlands contains important bias in our results.

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Appendix

TOTPAT95	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	1,423	2,758	0,629	1,094	1,401
$s\beta_0$	0,741	0,370	0,785	0,818	0,536
β_1 or α	0,566	0,099	0,173	0,151	0,162
$s\beta_1$ or $s\alpha$	0,121	0,017	0,032	0,033	0,025
R^2	0,251	0,353	0,311	0,248	0,399
Log-likelihood	-102,66	-97,78	-99,86	-102,81	-95,29
S.E. of regression	1,137	1,057	1,090	1,139	1,019
Model p-value	1,60E-05	1,17E-07	9,34E-07	1,80E-05	9,92E-09

Table 4. General statistics for models with total patents as dependent variable for year 1995.

TOTPAT97	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	1,270	2,746	0,639	0,887	1,552
$s\beta_0$	0,395	0,181	0,405	0,414	0,263
β_1 or α	0,682	0,121	0,187	0,171	0,164
$s\beta_1$ or $s\alpha$	0,064	0,008	0,016	0,015	0,011
R^2	0,636	0,787	0,687	0,654	0,777
Log-likelihood	-61,76	-43,74	-56,71	-60,11	-45,44
S.E. of regression	0,618	0,472	0,573	0,603	0,484
Model p-value	6,50E-16	1,50E-23	4,68E-18	1,29E-16	7,84E-23

Table 5. General statistics for models with total patents as dependent variable for year 1997.

TOTPAT99	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	1,585	2,647	0,435	1,069	1,576
$s\beta_0$	0,454	0,207	0,416	0,465	0,263
β_1 or α	0,632	0,126	0,200	0,167	0,168
$s\beta_1$ or $s\alpha$	0,072	0,009	0,016	0,017	0,011
R^2	0,529	0,752	0,690	0,578	0,773
Log-likelihood	-75,38	-52,83	-60,68	-71,52	-49,75
S.E. of regression	0,721	0,522	0,584	0,682	0,499
Model p-value	1,04E-12	2,68E-22	5,73E-19	2,34E-14	1,32E-23

Table 6. General statistics for models with total patents as dependent variable for year 1999.

HTPAT95	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	-2,629	-0,609	-3,434	-3,132	-2,428
$s\beta_0$	0,865	0,415	0,93	0,954	0,607
β_1 or α	0,84	0,146	0,241	0,225	0,229
$s\beta_1$ or $s\alpha$	0,141	0,019	0,038	0,038	0,028
R^2	0,352	0,483	0,385	0,349	0,509
Log-likelihood	-113,01	-105,47	-111,23	-113,15	-103,7
S.E. of regression	1,327	1,186	1,292	1,33	1,155
Model p-value	1,23E-07	7,04E-11	2,09E-08	1,42E-07	1,24E-11

Table 7. General statistics for models with high-tech patents as dependent variable for year 1995.

HTPAT97	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	-2,263	-0,357	-2,894	-2,7	-1,689
$s\beta_0$	0,456	0,206	0,493	0,485	0,315
β_1 or α	0,916	0,165	0,242	0,227	0,211
$s\beta_1$ or $s\alpha$	0,073	0,009	0,019	0,018	0,013
R^2	0,708	0,845	0,719	0,713	0,805
Log-likelihood	-68,67	-47,77	-67,49	-68,21	-55,33
S.E. of regression	0,696	0,507	0,683	0,691	0,568
Model p-value	8,68E-19	1,26E-27	2,73E-19	5,52E-19	1,97E-24

Table 8. General statistics for models with high-tech patents as dependent variable for year 1997.

HTPAT99	$\ln GERD$	$\ln S \times \ln GERD$	$\ln I \times \ln GERD$	$\ln C \times \ln GERD$	$\ln NQ \times \ln GERD$
β_0	-1,864	-0,34	-2,895	-2,426	-1,506
$s\beta_0$	0,577	0,253	0,605	0,607	0,386
β_1 or α	0,875	0,172	0,255	0,225	0,216
$s\beta_1$ or $s\alpha$	0,092	0,011	0,024	0,023	0,016
R^2	0,571	0,791	0,631	0,593	0,725
Log-likelihood	-92,16	-67,06	-86,92	-90,29	-76,59
S.E. of regression	0,916	0,64	0,85	0,892	0,733
Model p-value	4,00E-14	8,80E-25	2,36E-16	6,43E-15	9,68E-21

Table 9. General statistics for models with high-tech patents as dependent variable for year 1999.