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Knowledge convergence in European regions: Towards a cohesion?

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Abstract

In a knowledge economy, it is interesting to see that the concept of knowledge cohesion is a fertile soil for research. Despite the ongoing interest in investigating whether economic cohesion has been achieved in Europe there is no research that looks at knowledge cohesion. Though it is difficult to investigate such an abstract concept one can look at a more concrete concept such as convergence. Using the European Union Framework Programme data from 1984 to 2016 and simple network analysis and regressions we show that there are signs of knowledge convergence within the NUTS2 regions of Europe. Despite the fact that the top performers persist over the years convergence is much stronger among the less developed regions.

Keywords: knowledge, convergence, cohesion, diffusion, Europe
JEL codes: D83, O33, R11

1. Introduction

The recent changes observed in the knowledge and learning economies is a result of increasing interaction occurred in the era of globalisation. This era witnessed the changing significance of codified and tacit knowledge as well as intellectual capital in the course of economic growth and development. In this context, knowledge diffusion is a central element of innovation. The European Research Area (ERA), proposed in January 2000 and conceptualised in Lisbon summit of March 2000, is the basic backbone of the knowledge generation and diffusion strategy of the EU. The basic aim of ERA is to combine European scientific and technological resources more effectively. This attempt of amalgamation produces considerable results for productive knowledge flows to increase the competitiveness of ERA with the rest of the world. Though started earlier, the framework programme is the key policy tool to fulfil this aim.

Given the importance of cooperation in the EU 2020 Strategy, investigating the patterns of cooperation and the knowledge flows between the nodes of the wider EU networks is integral for building economic, social and political strategies according to the recent ERA progress report (EC, 2017). The EU Cohesion Policy, which aims to reduce economic and social disparities among the EU regions, is one example of such strategies. While "economic cohesion" and "social cohesion" are integral parts of EU Cohesion Policy, it is interesting to observe that "knowledge cohesion" is a fertile soil for research (Akçomak and Müller-Zick, 2018). The fact that we live in a knowledge economy where knowledge is a strategic asset and learning is at the heart of business growth and economic development coupled with the priority given to the cohesion policy necessitates to investigate the existence of knowledge cohesion in EU. The main of this paper is to investigate whether there are signs of knowledge convergence as a first step of knowledge cohesion.

This paper is an analytical attempt to discuss the knowledge flows at the regional level within EU in general. While doing so, it employs two concepts: knowledge cohesion at the mega level and knowledge convergence at the macro and meso levels. Next section is devoted to the theoretical discussion on why knowledge and its flows matter for economic growth and development and try to conceptualise knowledge cohesion. Section 3 describes the data and the methodology. Section 4 focuses on the analysis of the empirical results that mainly utilises micro data from framework programmes and look for evidence for convergence. The findings are summarised in section 4 and policy implications of the analyses is put forward in the concluding section.

2. Knowledge flows and knowledge convergence

Knowledge was not often studied by economists before 1980s though it is one of the central concepts in social science even going back to Plato and Aristotle. Before 1980s, the studies are indirectly engaged with the role of knowledge in the cases of human capital, research and development and technology. The rising interest especially in the last two decades is the result of globalisation and ever-increasing role of knowledge in the competitive position of countries and regions as an input to innovative activities. In this process, we observe a rise in the number of theoretical and empirical attempts on the commodification of knowledge. In order to be treated as an economic good, knowledge must be out in a form that allows it to circulate and be exchanged. One of the main distinguishing stylised facts about knowledge is that both its use and exchange value increase with its consumption since this process fuels the generation of new knowledge. The key transformation is the codification of knowledge. Through this process, it is objectively possible to measure and assess the impact of existing and new knowledge. Moreover, the output of this process is reduction of knowledge to the messages that employed by decision agents to shape their acts. However, there always remains a tacit component of knowledge. Not all but considerable amount of tacit component can also be transferred from one agent to others such as through common labour pools. In any case, either codified or tacit, flow, diffusion and further generation of knowledge necessitate social interactions and a systemic reliable process. The increasing significance of collaboration in R&D activities and positive contribution of knowledge sharing seemed to be considered as a vital process. Moreover, the importance of connecting industry and university R&D activities are treated as a prerequisite for economic performance. This explains why framework-like programmes are always on the policy agenda on a global scene.

Granovetter (1973; 1983) conceives the role of information and knowledge in the context of social network theory. The basic premises of these two studies may also provide evidence on how the knowledge in the networks, such as framework programmes or co-authorship networks, flows and is reproduced. What is striking is that instead of small well-defined groups Granovetter (1973; 1983) focuses on weak ties for the relations between groups. Following Granovetter (1973; 1983), we observe various applications of social network theory in the literature (e.g., Ahuja, 2000; Ozman, 2009; Partanen et al., 2014). More comprehensive account of the impact of knowledge and learning is put forward by the evolutionary economics. Lundvall and Johnson (1994) underlines that knowledge is the main factor of production and learning is the most important process. They assumed that the stock of knowledge is determined by two flows, namely learning and forgetting (p. 31). In this context, knowledge lost its value when it is not used. It has to be kept by the process of remembering. Learning as an interactive social process necessitates social interaction at different levels. The fundamental characteristics of a learning economy is its gradual and systematic development of its capability to learn (p. 32). This process drives technical change and growth. The 'learning economy' is a mixed economy in a fundamental sense that needs government intervention to stimulate the stock of knowledge. This evolutionary tradition is enriched with both theoretical discussions and empirical evidence (Lundvall and Archibugi, 2001; Christensen and Lundvall, 2004; Lorenz and Lundvall, 2006; Lundvall, 2016).

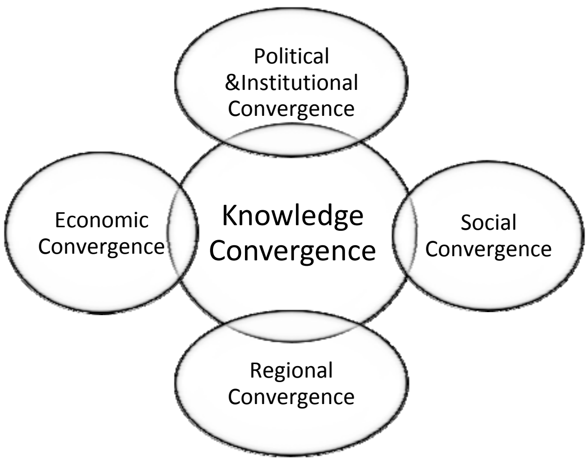
The evolutionary tradition also searches for an answer for the differences between developed world and developing countries concentrating on the peculiarities of developing countries (Lundvall, et al., 2006; Lundvall, et al., 2009; Lundvall, 2016). Though from the same tradition, Viotti (2002) criticises the use of the national systems of innovation concept for the developing countries. Viotti (2002) proposes that there are great differences in the process of technical change between industrialised countries and late industrialising economies. In the late industrialising countries, the process of technical change is characterised by process of learning rather than process of innovation. Therefore, he proposes a new definition of learning, "…*as the process of technical change achieved by the absorption of already existing techniques, i.e., of innovations engendered elsewhere, and the generation of improvements in the vicinity of the acquired innovations*" (Viotti, 2002: 658). Such learning ends up with the diffusion of technical change and incremental innovation. This type of learning is somewhat a "passive" process characterised by a passive National Learning Systems (p. 665). Viotti (2002) further differentiates the basics of passive and active learning and provide country examples. Although Viotti (2002) provides constructive insights, we do not believe such a taxonomy since national learning systems is a sub-system of national innovation system in which one can find examples of passive and active learners inside the system.

The next question, in fact, builds up the skeleton of this paper. How do national innovation systems converge to each other through interactive learning and what is the role of knowledge convergence in this process? The first step to answer this question is to develop a conceptualisation for knowledge convergence. This conceptualisation brings about the discussion on collaborative learning. "*Collaboration is a coordinated and synchronous activity that is the result of a continued attempt to construct and maintain a shared conception of a problem*" (Roschelle and Teasley, 1995:70). In this process, learners generate knowledge by working on complicated problems together and finding solutions through collaborative learning. The mutual interaction enables knowledge exchange and, in turn, knowledge convergence in time. One approach of conceptualising knowledge convergence utilises the concept of knowledge contribution equivalence in which learners may contribute ideas to varying or similar extents (Weinberger et al., 2007). In the literature, two different yet complementary measurement methods are introduced to analyse the knowledge convergence processes, namely the knowledge level approach and the trans activity approach (Weinberger et al., 2007:418). The knowledge level approach allows an analysis of the type of knowledge, that is knowledge of the task and knowledge of the team, which must be shared in order to improve team performance
(Cannon-Bowers and Salas, 2001). The trans activity approach suggests analysing learners' social mode of co-construction, depicting how strongly and in what ways learners refer to the contributions of their learning partners (Teasley, 1997). Trans activity is the degree to which learners refer and build on others' knowledge

contributions and has been found to be positively related to individual knowledge acquisition in collaborative scenarios (Teasley, 1997). Furthermore, learners can also build a consensus in various ways through quick, integration-oriented or conflict-oriented consensus building (Weinberger and Fischer, 2006; Weinberger et al., 2007). This paper employs the insights provided by these two approaches. In sum, we can define knowledge convergence as the growth and intensification of common shared knowledge that brought by all the collaborating partners.

The European example is a typical one in the context of knowledge convergence that has an impact on the convergence of national systems. The Lisbon strategy can be treated as an important step towards convergence at different levels such as political, economic, social, institutional, regional and knowledge. All these types of convergences are indispensable elements for building a cohesive union. We observe a general tendency in Europe in accordance with the prepositions of trans activity approach. In fact, all types of convergence feedback each other and knowledge convergence is glue for overall convergence and cohesion as can be seen from Figure 1. The shared knowledge in the system reproduces itself, causing agents to develop a unique jargon and find similar solutions to similar problems. This knowledge convergence process enables other types of convergences and ultimately cohesion in the long run.

Figure 1: Interdependence between Various Types of Convergence



Godinho and Mamede (1999) put forward a taxonomy of convergence with three different versions (cited in Tomlinson, 2006), namely unconditional convergence, conditional convergence, and divergence. In the case of unconditional convergence, less developed economies are expected to converge with more developed ones. Social capabilities cause some countries to mobilise and utilise resources but not others for conditional convergence. Finally, there may be tendencies for some economies or regions to diverge instead of convergence. Some resources are concentrated in particular places such as labour supply, localised knowledge spillovers, and supply of inputs. This concentration creates industrial cores that would produce divergence rather than convergence in the periphery (Tomlinson, 2006). We suppose that knowledge convergence is more easily realised through the interactions of regions rather than nations. This process of regional knowledge convergence helps to national knowledge convergence to lessen disparities and inequalities. Therefore, the stakeholders of the ERA will benefit from knowledge flows for conditional and unconditional knowledge convergence. Cantwell and Janne (1999) and Cantwell and Iamarrino (2001) are the early examples of how leading multinational firms from the major European centres in their industry tend to carry out technological activity abroad, which is relatively differentiated from their domestic technological strengths. Caniels and Verspagen (2001) describe a model for knowledge spillovers based on learning capability of a region and the rate of knowledge generation through R&D. According to results of the study, borders between countries considered as barriers to spillovers and random differences in terms of structural characteristics may promote peripheral regions and cause them become local centres. For European integration, this result underlines the importance of regional policies in establishing local growth poles and increased prosperity around them (Caniels and Verspagen, 2001: 326).

By using European regional patent dataset and tools of social network and multivariate analysis, Ho and Verspagen (2006) identified higher order regional innovation systems as the key hubs from which knowledge flows in the European innovation system. These hubs considerably shorten the distance for the receiving regions. According to results, ERA network is heterogeneous in terms of density and global connectivity. Therefore, different types of policies should be used for lower and higher order regional innovation systems. The role of lower order systems is crucial for local development while higher order systems are critical both for the performance of the system as a whole and knowledge diffusion inside ERA (Ho and Verspagen, 2006). These higher order systems act as decisive actors for knowledge cohesion.

3. Data and methodology

To investigate whether there is knowledge convergence in Europe we benefit from the EU FP data from the first round (FP1, 1984-1987) till the last round (FP8 -H2020, 2013-2020). FP data is rich, enables comparison over time, covers a wide range of scientific areas and the selected projects reflect scientific issues at the world frontier. Thus, the analysis of the whole FP data can tell a lot about where knowledge is created and with whom.[1] Section 3.1 presents basic information on the FP, detailed information on the raw data collected and the actual data used in this research. Section 3.2 explains the methods used to analyse the data.

[1] A similar analysis can also be conducted using scientific publication data. However even a much shorter period from 1996-2016 requires analysis of 15.6 million papers (according to Scimago) and associated co-authorship network which is out of the scope of this research. Besides there are various issues of quality, missing information and scientific field specific issues that would cause problems in interpretation.

3.1 Data

The FP data used in this research is downloaded from the European Union Open Data Portal.[2] Table 1 presents summary statistics for each FP round. The figures displayed in parentheses indicate the number of projects used in the calculation of their respective column.[3] The same approach was also used in the calculation of the average cost and funding of the projects. According to the data, number of projects in all rounds increased, except for FP6.[4] Projects with the longest duration were implemented in the 5th FP round. The projects realised in FP6 display a significant difference from the others. In FP6, both the average cost of the projects (4,135,682.23 €) and the amount of EC contribution (1,853,125.80 €) are the highest among all FPs. On the other hand, when the EC contribution per project is proportioned, it is found that the average financial support received by FP6 projects (44.80%) is lower than the other FP projects. The highest ratio of financial support per project is provided in FP7 (73.24%). When the FP data is analysed in a nutshell we can say that there are two structural breaks in the programme, first from FP3 to FP4 where the overall funding more than doubled and from FP6 to FP7 where the overall funding almost tripled. Given that the average cost and funding figures do not display such sharp changes we can expect that increased funding would lead to more projects being financed, increased number of nodes (project partners) and increased number of connections between partners which would mean a denser network over the years. In order to demonstrate how the FP densities increased, partial network graphs have been plotted for FP2 and FP7 using only 2.5% of the links. Comparing the two figures it is clear that the network density has increased over the years.[5]

In order to implement network analysis, data obtained from European Union Open Data Portal were edited for each FP round. First of all, projects for which no spatial data can be obtained were removed from the database. Afterwards, NUTS 2 (LAU 2 – NUTS 2013, EU-28, 2016[6]) equivalent of the spatial information of each project partner was found. Lastly, making use of the NUTS II data of project partners, networks were plotted for each FP and related network statistics calculations were implemented.

The additional data that are used as control variables such as the patents per million inhabitants in 2005, R&D expenditures per million inhabitants in 2007 and human resources in science and technology per million inhabitants in 2006 are gathered from the Eurostat database. Using the raw data of FPs has the advantage of calculating the network statistics for almost all the NUTS 2 regions. However, patent, R&D and human

[2] https://data.europa.eu/euodp/en/data/dataset?q=cordis.
[3] For instance, in the downloaded raw data, there are 5,527 project records for FP3. However, average duration (931.29 days) is calculated over 5,236 projects because the start and end dates of the remaining projects are not found in the raw data.
[4] We do not include H2020 in such interpretations as the programme is still in progress.
[5] The figures are supressed due to space limitations but are available on request.
[6] http://ec.europa.eu/eurostat/web/nuts/local-administrative-units

resources data is available only for about 70-80 percent of the NUTS 2 regions if data around (and after) the year 2005 is used. The use of data for earlier periods is not possible due to data limitations.

Table 1: EU Framework Programmes, 1984-2016

Title	Period coverage	Budget (in billions of Euros)	# of Projects	Average Duration of the Projects (day)	Average Cost of the Projects	Average Funding of the Projects
FP1	1984-1987	3.3	3,282	1,073.74 (3,281)		
FP2	1987-1991	5.4	3,896	1,010.23 (3,452)	1,089,751.97 (187)	536,459.01 (188)
FP3	1990-1994	6.6	5,527	931.28 (5,236)	1,435,484.87 (550)	1,031,637.3 (1,089)
FP4	1994-1998	13.2	14,567	831.29 (13,676)	1,968,140.19 (3,772)	913,115.88 (4,027)
FP5	1998-2002	14.9	17,202	1,358.43 (16,121)	1,381,296.12 (15,441)	816,407.6 (15,439)
FP6	2002-2006	19.3	10,091	991.19 (9,903)	4,135,682.23 (6,363)	1,853,125 (9,578)
FP7	2007-2013	55.9	25,607	1,196.01 (25,472)	2,358,498.29 (25,054)	1,727,511 (25,472)
H2020	2014-2020	80.0	9,055	1,088.14 (9,055)	2,101,884.92 (9,055)	1,712,488 (9,055)

Source: EU Research Framework Programmes 1984-2014, Horizon Magazine Special Issue, March 2015 and authors' own compilations.
Note: FP4 data is not covered in this research because the data do not have regional identifiers.

3.1 Methodology

The methodology rests on three connected parts. First, we use several network statistics and look at the overall network. Second using four network statistics that can be used as proxy for knowledge exchange we look for signs of knowledge convergence. Third, a number of robustness analysis is conducted to increase the validity of our results.

First of all, the overall data is analysed using several network statistics such as the number of nodes, unique edges, distance measures and centrality measures (Wasserman and Faust, 1994; Scott, 1991). The statistics are provided for each round of FP which not only helps us to understand the overall network but also shows the development over time. Section 4.1 presents the results interpreting the network statistics.

The network analysis on the raw data produced four network statistics that we base our investigation on: *(i)* network degree that represents the number of links that are linked to a node. The more a node is connected the more the opportunities to access to a larger knowledge base, *(ii)* betweenness centrality that shows the node's importance in the overall connectivity of the network which is defined as the fraction of the shortest paths between any pair of nodes in the network, which pass through the *nth* node, *(iii)* closeness centrality that denotes the sum of theoretical distances from a node to all other nodes in a network. Being closer to other nodes would prove to be beneficial in terms of early access to knowledge, *(iv)* eigenvector centrality that shows the importance of a node in a network based on a node's connections. Playing a bridge or a gatekeeper role among "important" nodes would bestow advantages, especially in terms of easy access to knowledge.

Second, these four network statistics are used to investigate knowledge convergence in a more detailed manner. The aggregated data present four network statistics at the NUTS 2 regional definition which are not comparable across FP periods because the network is different in each round. Thus, for each variable and for each FP period the data is divided in to 100 percentiles to arrive to a measurement unit, which is comparable across FP periods. To give an example, the betweenness scores of Germany DED2 Dresden region in FP2 and FP7 are not comparable but Dresden was only in the 22nd percentile in FP2 but reached to 80th percentile in FP7. In terms of being a hub of knowledge exchange Dresden moved from bottom to top in about 20 years comparing FP2 to FP7, which is an achievement. There are also regions that lost significance as being a knowledge hub such as DE72 Giessen moving from top 30 to bottom 40 percentiles, or FR41 Lorraine moving from top 78th to bottom 40th percentile.

Once percentiles of each variable for each FP period are calculated the data set is comparable across FP periods. As a sign for knowledge convergence we looked at the relation between change in percentile rank over the years and starting level percentile rank for the four network statistics defined above. The idea originates from the convergence of income. A statistically significant negative coefficient of a simple correlation between percentage change of GDP in two time periods and starting level of GDP is accepted to be a sign for convergence (e.g., Barro, 1991; Armstrong, 1995; Sala-i-Martin, 1996; Fagerberg and Verspagen, 1996). To increase the coverage, we first look at the relation between change in percentile rank from FP5 (1998-2002) to FP7 (2007-2013) and the percentile rank in FP5. We did not include FP1, though we have the data, because the programme was new and its budget and scale were limited. In a similar manner, we did not include the first wave of H2020, though we have the data, because H2020 has just started. The results are presented in simple scatter diagrams using four different network statistics. Moreover, we report the coefficients of a simple Ordinary Least Squares (OLS) where we regress change in percentiles on starting level percentile rank and country dummies. As in the case of convergence in GDP a statistically negative sign of the coefficient of starting level percentile signal convergence in knowledge among European regions.

Third, several robustness analyses are performed to validate the results. The OLS results for knowledge convergence can be sensitive to additional control variables that reflect the science and technology base of a region. Thus, as an initial attempt we included indicators of patent applications, R&D expenditure and human resources in science and technology to control for the differences in knowledge base. Then the convergence hypothesis is also tested in a much longer period from FP2 (1987-1991) to FP7 (2007-2013). Despite loss of observations looking at the longer period has advantages. It could be the case that convergence is more visible over a longer period especially in case of knowledge which takes time to accumulate. This longer period from FP2 to FP7 excludes less developed regions and the sample becomes more homogenous. Thus, the probability of obtaining a negative significant coefficient for the level variables in a homogenous sample may reduce. Finally, the analysis is replicated for the NUTS 1 regions to see whether the results survive if regional definitions change.

4. Results

4.1 Network results

Table 2 shows that the number of nodes participated in the FP has increased over the years. This shows that the FP has gained wide acceptance and participation in the programme became prevalent. Starting from FP1, value of average degree rises, which means that the capacity of regions increases in terms of maintaining links with others. Number of unique and duplicated edge values increase from FP1 to FP7. Increase of unique edge ratio within the total edges (unique and duplicate) show whether the structure supports establishment of links -*i.e.* project partnership- among actors without previous linkages. Otherwise, if the unique edge ratio within the total edges decreases, this will show that the structure supports project partnership among those, which previously formed project partnerships. The increase in the ratio of duplicate values is much higher than that of unique values, which can be explained using the notion of path dependency and preferential attachment. Experience in past projects may decrease transaction costs among partners in subsequent partnerships, which may augment mutual trust and understanding, as well as future collaborations.

The ratio of self-loop value in each FP to the number of edges is used to understand whether there is regional favouritism. The lowest ratio is found in FP7 (0.034) and the highest ratio in FP1 (0.111). Although the number of organisations that are capable and willing to participate in FP changes over time from region to region, the decrease in value from FP1 (0.111) to FP7 (0.034) and the decrease of the path length or its stability demonstrate that the regions increasingly approach more positively towards cooperation with other regions. This result is considered to be in line with EU's aims of popularising FP and making it common practice for parties to work together.

Average geodesic distance (path length) decreases from 1.94 to 1.45 through FP1 to FP7. which shows that the distance between actors is shortened and the network structure increasingly supports knowledge transfers and cooperation. This is a rather significant finding. One of the most significant inputs in the emergence of innovation is the cooperation of actors having different resources; such as knowledge, capability, etc. The gradual decrease of the distance among actors over time shows that different actors came together as well as that this process supports the emergence of innovation.

Table 2: Network statistics

	FP1	FP2	FP3	FP5	FP6	FP7	H2020
Graph Type				Undirected			
Nodes (Vertices)	182	216	245	312	322	336	324
Unique Edges	1,272	2,994	3826	5,674	5,613	5,749	6,265
Edges with Duplicates	11,818	73,653	130,260	417,130	591,753	774,172	193,349
Total Edges	13,090	76,647	134,086	422,804	597,366	779,921	199,614
Self-Loops	1,448	3,673	6,537	18,513	20,172	36,111	8,510
Average Geodesic Distance	1.94	1.60	1.54	1.46	1.43	1.45	1.61
Graph Density	0.18	0.41	0.46	0.54	0.56	0.55	0.40
Average Degree	32.81	89.79	113.32	168.33	182.80	186.00	131.43
Average Betweenness Centrality	86.18	65.02	67.18	72.86	70.25	75.65	97.40
Average Closeness Centrality	0.003	0.003	0.003	0.002	0.002	0.002	0.008
Average Eigenvector Centrality	0.006	0.005	0.004	0.003	0.003	0.003	0.003
Average Clustering Coefficient	0.64	0.77	0.81	0.84	0.85	0.85	0.78

The density of the network from FP2 onwards seems to be fixed at 0.50. The existence of regions that have not yet cooperated with each other as partners within any FP throughout all FPs that have been implemented for over 30 years, brings to forth the necessity for a reconsideration of the policies Europe implements for cohesion. Additionally, we see an increase in average betweenness centrality (Borgatti et al., 2013) and decrease in average closeness centrality (Newman et al., 2003) values. This change also demonstrates that the newcomers, in general, link to the periphery of the network. Actors with high eigenvector value also fill in the structural holes in the network by setting links with important actors, i.e., actors with the highest number of links. Differently, these actors are considered to have more access to codified knowledge compared to others. Moreover, the decreasing average path lengths and increasing clustering values of FPs show that a small-world network emerged from the structure.

Such type of networks, which have relatively high clustering coefficients and short path lengths, supports knowledge creation and knowledge diffusion (Cowan, 2004).

Table 3: Variety of the Regions Cooperated with

	FP1	FP2	FP3	FP5	FP6	FP7	H2020
Average Density	0.180	0.413	0.460	0.534	0.562	0.548	0.402

Note: Calculated by excluding the links established with the actors in the same region.

Another important point is to look at the link establishment preferences of the nodes. It is assumed that along with actors' increasing number of links in time, their preference to establish links with different actors allowed for the formation of knowledge cohesion at least to some degree. In order to calculate this, the number of different nodes that the nodes in the FP cooperated through project partnerships has been found and the result is proportioned to the potential number of partnerships that could be established with different actors in that FP. In other words, the results of the density calculation excluding the links that the actors form with the actors in their own region, are given Table 3. This presents the average density of all regions in each FP round. The upward trend observed in average density demonstrates the formation of at least a minimum level of knowledge convergence among different regions in terms of knowledge level, which encourages strengthening of relationships and development of trust-based relationships and facilitates tacit knowledge transfer.

4.2. Persistence of top players and the OLS results

The recent uptake of the persistence story shows that the starting levels are an important determinant of the current situation for a variety of cases (e.g., Acemoglu, 2001; Guiso, et al., 2016). Due to economic and cultural factors some regions are more innovation prone compared to others (Rodriguez-Pose, 1999). Such factors give a head-start to some regions in terms of knowledge generation which may persist over the years. Thus, we expect to see that the list of top performers remained stable over the years.

For each FP round the regions are ranked according to network degree that shows the number of direct links to other regions. For instance, the maximum degree of FP7 belongs to FR10 *Île de France* which means that FR10 is connected to 329 regions out of the 349 available. Table 4 lists the top 5 percentile EU regions according to network degree and Table 5 according to betweenness centrality that shows how central a region is in knowledge flow in a network. It could be the case that a region with even low number of degree connects important nodes in the network thus has a more central position compared to others.

As can be seen from Tables 4 and 5, there is high association between the top 5 percent lists of degree and betweenness. The pairwise correlation coefficients of degree and betweenness in different FP periods range from 0.62 to 0.78 all of which are significant at the 1 percent level. The within correlations of degree and betweenness for different FP periods are expectedly high. The correlation coefficient of network degree for different FP periods ranges from 0.63 to 0.96 and for betweenness ranges from 0.78 to 0.97 all of which are significant at the 1 percent level.

Table 4: Top 5 percentile EU regions according to network degree

FP1	FP2	FP3	FP5	FP6	FP7	H2020
FR10	FR10	FR10	FR10	FR10	FR10	ES30
UKI	ES30	EL30	ES30	ITE4	BE10	FR10
UKJ1	NL31	PT17	PT17	EL30	UKI	UKI
FR71	PT17	ITC4	EL30	ES30	ITE4	BE10
DK01	ITC4	NL31	UKI	DE21	ES30	ITE4
NL31	EL30	IE02	FR71	ITC4	EL30	NL31
ITC4	UKI	FR71	ES51	ES51	DE21	ES51
BE10	FR71	ES30	NL31	UKI	ES51	DE21
EL30	IE02	UKJ1	ITE4	AT13	NL31	EL30
DE21	BE10	UKI	ITC4	HU10	AT13	ITC4
	DK01	DK01	DE21	BE10	ITC4	PT17
	DE21	ITE4	FI1B	NL31	DK01	AT13
		ES51	SE11	PT17	SE11	IE02
		DE21	DK01	PL12	FI1B	DEA2
			BE10	IE02	DEA2	FI1B
			IE02	SE11	ES21	ES21
			DEA2	FI1B	IE02	NL32
			ITD5	NL22	PT17	DE30
						RO22

For a more detailed look, it is better to limit the analysis to FP2-FP7 because FP1 marks the introduction of the framework projects and H2020 has started only few years ago. We took FP7 period which turns the largest top 5 percentile regions as benchmark and looked at the percentiles of the regions over the FP2-FP7 period using network degree. Except 3 regions all others were at least at the top 15 percentile in any FP round which indicates that the top performers do not change. There are three success stories within the top 5 percentile performers which are SE11 *Stockholm* that moved from 77th to 96th percentile; AT13 *Wien* that moved from 46th to 98th percentile and ES21 *País Vasco* that moved from 73rd to 96th percentile between FP2 and FP7. When a more limiting period is considered from FP5 to FP7 the persistence of top performers is more visible. Within this period top performers' percentile score ranges from 92nd to 100th percentile. When betweenness centrality is used instead of network degree the results are qualitatively similar except the appearance of regions in less developed countries which is a finding towards knowledge convergence. Though HU10 *Közép-Magyarország*, PL12 *Mazowieckie*, CZ01 *Praha*, SI02 *Zahodna Slovenija* EE00 *Eesti,* and RO22 *Sud-est* joined the EU and the FP at a much later stage and had very low percentile scores in FP3 they become top performers consistently in the last two rounds FP6 and FP7. The percentile scores of these regions in the last three FP rounds ranges from 84th to 96th percentile.

Table 5: Top 5 percentile EU regions according to network betweenness centrality

FP1	**FP2**	**FP3**	**FP5**	**FP6**	**FP7**	**H2020**
FR10	FR10	NL31	FR10	FR10	FR10	TR51
UKI	FR71	EL30	PT17	DE21	BE10	ES30
ITE4	IE02	UKI	NL31	UKJ1	ES51	UKI
DK01	DEA2	FR10	EL30	ITE4	UKI	FR10
PT17	ES30	PT17	ES30	AT13	DE21	DE21
UKJ1	UKI	FR71	UKI	EL30	EL30	ES51
FR71	PT17	ITC4	FR81	HU10	ES30	BE10
NL31	ITC4	DE30	ES51	ITC4	PT17	PL22
BE24	NL31	ES30	ITE4	ES30	NL31	ITE4
ITC4	EL30	ITE4	FR71	UKI	UKJ1	EL30
	DE21	DE21	FI1B	ES51	ITE4	PT17
	DE71	IE02	ITC4	BE10	DE30	NL31
		NL22	UKJ1	PL12	AT13	PL12
		ITC1	ITD5	FI1B	EE00	ITC4
			DE21	RO22	IE02	AT13
			ES21	NL22	PT11	IE02
			EL12	PT17	NL32	DE71
			SE11	SI02	DK01	DE30
				CZ01	FI1B	EL12
					ITC4	

Thus, looking at the top 5 percentile regions we can conclude that the top performers do not vary much in the last 25 years which suggests that top knowledge hubs are persistent over the years. However, the new emerging knowledge hubs in Czech Republic, Estonia, Hungary, Romania and Slovenia especially in the last three rounds of FPs may be taken as a sign of knowledge convergence.

Applying the convergence idea in empirical growth models to our case we look at the relation between changes in percentiles of the four network statistics over the FP5-FP7 period and relate them to their respective starting level (FP5) statistics. This period is specifically selected because using an early FP round significantly reduces the number of observations and do not include less developed countries integrated to Europe at a later stage. If there are signs of convergence within this short period where competition in obtaining funds was tight we can assume that there will be convergence in a much longer period. For consistency and robustness, we report the same analysis for network degree, betweenness, closeness and eigenvector centrality statistics. In fact, the robustness analysis in this section over the FP2-FP7 period supports this argument (see section 4.3). Figure 2 shows the result of this analysis.

In Figure 2 all four panels display a negative correlation indicating convergence. Thus, on average, regions that were less endowed in terms of knowledge caught up regions that were more endowed in terms of knowledge. Three observations can be made from Figure 2. First, the convergence story holds no matter what network statistics we use which introduces further robustness to our analysis. Second, complementary to the previous discussion on top performers there is almost no convergence in top 10 percentile regions. In all four panels the variance beyond 90th percentile is very low indicating that top 10 percentile performers do not change that much over the years. Lastly, we see the variance increases as we move down to lower percentiles which indicates that the performance of regions in the lower 40 percentiles can vary in great extent.

The convergence story can be statistically tested using simple OLS regressions. The differences in percentiles in four network statistics from FP5 to FP7 are used as dependent variables where positive values indicate better performance in terms of network structure. The starting level percentile of each network statistics are used as independent variables. The OLS regressions always include country dummies to control for country fixed effects and robust standard errors to account for heteroscedasticity. 4 OLS regressions are estimated for each network statistics for the FP5-FP7 period. The estimations cover more than 300 NUTS2 regions in 30 countries which accounts to about 90% of all NUTS2 regions. The results are summarised in Table 6. Regardless of the network statistics the results indicate that there is knowledge convergence among European regions. It is surprising to see that even in these simple OLS analyses the fit of the model is rather high.

Figure 2: Knowledge convergence in European regions FP5 to FP7, 1998-2013

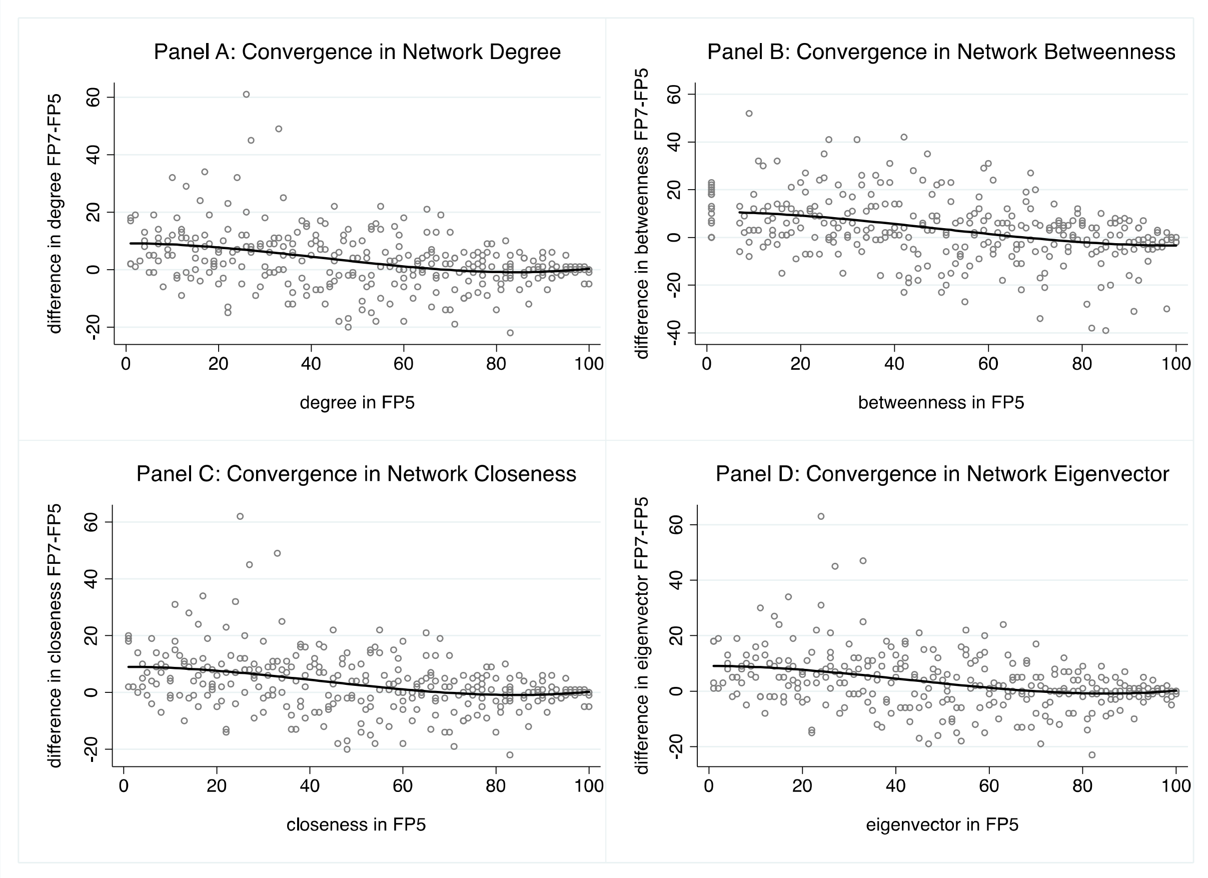


Table 6: Summary results of the OLS analysis for convergence, FP5 to FP7

	Change in percentile FP5 to FP7			
	degree	betweenness	closeness	eigenvector
level of FP5 percentile	-0.075*** (0.016)	-0.148*** (0.023)	-0.074*** (0.015)	-0.073*** (0.015)
Country dummy	YES	YES	YES	YES
R-squared	0.46	0.32	0.46	0.47
N	306	306	306	306

Note: Detailed OLS results are suppressed but available on request. Each column presents an OLS regression where the dependent variable is indicated on the top row. Numbers in parentheses are robust standard errors. *** indicates the estimated coefficient is statistically significant at the 1 percent; ** at the 5 percent and * at the 10 percent level.

In summary, the simple analysis in this section shows that there are signs of knowledge convergence in European regions. Regions that are endowed less in terms of knowledge tend to build up capabilities and catch-up regions that are rich in terms of knowledge which definitely will help European integration. Despite the fact that the top performers persist over the years, knowledge convergence is much stronger among the less developed regions.

4.3 Robustness

To carry the analysis a step further we replicate the analysis in Table 6 for only the betweenness centrality measure and include additional control variables that can explain the variation in change in percentile score from FP5 to FP7. It is rather difficult to find statistics at the NUTS2 level especially for earlier periods. Thus, to maximise the number of observations we select the midpoint of the period as benchmark and gathered information on three science, technology and innovation (STI) related indicators: patents per inhabitants in 2005; human resources in science and technology per inhabitant 2006 and R&D expenditures per inhabitant in 2007. However due to data limitations the analyses were conducted in a smaller group of NUTS2 regions where the number of observations is in the range of 250 compared to over 300 in Table 6. The results of this extended analysis are displayed in Table 7. Regardless of the estimation the coefficient of the level of FP5 percentile remains negative and statistically significant. Columns (2) to (4) report estimations where three STI indicators are introduced individually. As expected all three indicators are positively associated with change in percentile scores. Due to high correlation between these indicators we only report two other estimations in columns (5) and (6). The results do not change.

Table 7: Extended results of the OLS analysis for convergence, FP5 to FP7

	Change in betweenness percentile FP5 to FP7					
	(1)	(2)	(3)	(4)	(5)	(6)
Level of FP5 percentile	-0.148*** (0.023)	-0.169*** (0.026)	-0.194* (0.033)	-0.198* (0.032)	-0.191*** (0.032)	-0.201*** (0.035)
Patent		0.015** (0.007)			0.012* (0.007)	
HRST			0.493*** (0.175)		0.304** (0.165)	0.129 (0.189)
R&D				0.006*** (0.002)		0.006** (0.002)
Country dummy	YES	YES	YES	YES	YES	YES
R-squared	0.32	0.33	0.35	0.33	0.33	0.33
N	306	257	263	239	245	234

Note: Detailed OLS results are suppressed but available on request. Each column presents an OLS regression where the dependent variable is indicated on the top row. Numbers in parentheses are robust standard errors. *** indicates the estimated coefficient is statistically significant at the 1 percent; ** at the 5 percent and * at the 10 percent level.

In section 4.2 the convergence story was built on a comparison between FP5 and FP7. What if we extend the period and look at FP2 to FP7? This analysis is particularly interesting because more developed countries (EU15) were funded in the earlier rounds of the FP. While a longer time period increases the probability of obtaining evidence for much stronger convergence, the homogeneity of the sample of regions from richer countries reduces it. Table 8 shows the results of this robustness analysis. Within a sample of much more developed regions the findings towards convergence are exacerbated. As can be seen from Table 8 the correlation is much stronger and the fit of the model increases considerably when a longer but more homogenous sample is used.

Finally, one could wonder whether the results are affected when regional definitions are changed. The analyses are replicated for NUTS 1 regional definitions. For this the raw data is compiled at NUTS 1 level and all network statistics are calculated again for about 120 regions. The convergence story is tested in a similar manner using simple OLS regressions with country dummies for the FP5-FP7 period, extended analyses including additional control variables and finally extending the period of analysis to FP2-FP7. Overall the findings indicate that knowledge convergence story is robust to change in regional definitions.[7]

Table 8: Summary results of the OLS analysis for convergence, FP2 to FP7

	Change in network statistic FP2 to FP7			
	degree	betweenness	closeness	eigenvector
level of network statistic FP2	-0.258*** (0.032)	-0.284*** (0.033)	-0.257*** (0.032)	-0.254*** (0.032)
Country dummy	YES	YES	YES	YES
R-squared	0.70	0.65	0.70	0.71
N	214	214	214	214

Note: Detailed OLS results are suppressed but available on request. Each column presents an OLS regression where the dependent variable is indicated on the top row. Numbers in parentheses are robust standard errors. *** indicates the estimated coefficient is statistically significant at the 1 percent; ** at the 5 percent and * at the 10 percent level.

5. Conclusion

Flows of knowledge, created through the interactions between intellectual capital and physical capital, are ever more seen as being the main pillar of the modern era. The conversion of knowledge and new ideas into commercial products and services and rise in the number of actors facilitating these conversion activities, is critical for economic

[7] The analysis at the NUTS 1 level is not presented due to space limitations but are available on request.

growth and development. The systematic and reliable processes enable collaboration among the agents and create an ecosystem suitable for knowledge convergence. The successful knowledge convergence narrative, in turn, provides drivers for knowledge cohesion to decrease regional disparities. In order to unlock development potential at the local level, much of the local knowledge does not pre-exist exogenously either locally or centrally. The knowledge needed for this change can only be generated by means of a deliberative process of debate and engagement between local, regional and central parties, actors and institutions with different interests, preferences and competences (McCann, 2015).

This study is an attempt to present knowledge convergence as realised between regions of EU and knowledge cohesion as a possibility for EU in general. In the empirical part of the study, the increasing number of nodes and links demonstrate that the regions in Europe display an increasing tendency to participate into FPs. On the other hand, the changes in closeness, betweenness and eigenvector values show that the new participants enter into the network generally by linking to the regions which have vast experience in FPs (i.e., preferential attachment). As a result, while this process increases the sustainability of the structure; at the same time, diversification of the linked nodes shows us there is at least a minimum level of knowledge cohesion that began to be formed among these nodes. Had the newcomers preferred to establish links only with the regions that previously participated in a high number of projects, it might have been speculated that this relatively closed network (or the notion of path dependency), teaming up with previous partners, may not only lead to redundancy but also trigger the risks of lock-in (Leonard-Barton, 1992). Another important point is the increasing clustering value and decreasing path length which demonstrates that the structure is evolving into a direction supporting knowledge convergence.

The results of the network analysis are supported by a simple regression analysis in which we show that there is knowledge convergence among EU NUTS 2 regions. Even a very simple analysis controlling only for country fixed effects produces consistent results. The results are robust to inclusion of other control variables, change of period of analysis and change of regional definition. The results show that there is persistence in top 10 percentile regions meaning that regions that had good account in participation to FPs are still the usual suspects. However, when all the regions are taken in to account the results show that regions that were less endowed in terms knowledge seems to catch-up. To our knowledge this is the first research that looks in to the concept of knowledge cohesion and empirically show that there are signs of knowledge convergence. It is obvious that there is much to do conceptually and empirically to further develop the concept. Thus, knowledge cohesion and convergence seem to be a fertile soil for research.

EU cohesion policy has experienced a series of metamorphoses during its five programming periods since 1989 and become the most financed EU policy (Medeiros, 2017). The recent evidence shows that the policy has a positive impact on economic growth in all regions (Gagliardi and Percoco, 2017; Fratesi and Wishlade, 2017; Percoco, 2017). However, its impact together with Research and Innovation (R&I) policies seems to be conflicting in terms of convergence. Izsak and Radosevic (2017) conclude that these policies caused a further divergence between Northwest and South and convergence between Northwest and Central-East Europe. Moreover, the positive impact of cohesion policy tended to be more pronounced depending upon the geographical proximity of regions to urban agglomerates. Favourable geography and progressive suburbanisation or rural areas have increased the impact of the policy (Gagliardi and Percoco, 2017). Smart specialisation policies already developed is an attempt for the improvement of political infrastructure of new policies in the next programming period. It is in accordance with the objective of cohesion policy to reduce disparities among the EU regions as a key problem of regional innovation policy (McCann, 2015; McCann and Ortega-Argilés, 2013, 2015, 2016; Morgan 2015). The concept of smart specialisation is very much related with the knowledge ecosystem in which knowledge, technology and innovation generation and diffusion processes expedites entrepreneurship to unlock development potential of a region. The successful implementation of this idealisation in all regions, of course, ultimately produces results towards knowledge convergence. Moreover, the success also depends on proper functioning of both regional and national innovation systems. However, this is not always the case for laggard regions. Finally, the discussion on whether smart specialisation policy should focus on disruptive activities in the form of mission-oriented policies still continues in EU policy agenda (Mazzucato, 2013; Frenken, 2016; Balland, 2017). We consider that such a general approach creates too much burden and risks for the regions.

Medeiros (2017) provides a good account of European cohesion policy for the post-2020 period. Medeiros (2017) starts with presumption that the decisive target of EU policies is to promote territorial cohesion and development rather than growth. Based on this assumption, he proposed a “one goal-four targets” strategy, namely green economy, balanced territory, good governance and social cohesion. He further claims that build on Europe 2020 strategy, the proposed strategic framework brings “a clear territorial dimension” (p. 10). This strategic vision lacks to include knowledge cohesion into picture, though we see some components of knowledge cohesion. As we claimed in the introduction section, knowledge cohesion is a mega concept that links other types of cohesion. Therefore, this research suggests that the one-target formulation should be replaced as “territorial knowledge cohesion and development”.

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