European Knowledge Neighborhood:
Knowledge production in EU neighboring countries and intensity of the relationship with EU countries

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Abstract: This study aims at analyzing the creation of knowledge in the European neighborhood and the diffusion of knowledge among EU and ENC countries. We firstly describe national innovative activity in order to make available a comprehensive picture of this phenomenon in the European neighborhood.
A special attention is devoted to an extensive descriptive analysis of different channels of knowledge flows originating and most importantly destined to ENC's. We specifically focus on those channels which are based on interpersonal relationships between economic agents, scientist, researchers and innovators in EU and EN countries.
DEA analysis is finally employed to assess the efficiency performance of countries in the production of knowledge either measured by patents or by publications thanks to their investment in R&D and in human capital and to knowledge flows coming from abroad through different knowledge networks.

Keywords: European Union, European Neighbouring Countries, Knowledge Production Function, Knowledge flows, Data Envelopment Analysis

1. Introduction

According to both applied and theoretical economists, economic growth is not entirely dependent on traditional production factors such as physical capital and labour, but is increasingly related to the stock of intangible resources such as culture, competence, innovative capacity and knowledge.

European Union policy makers reached the same conclusion and have established several initiatives paying particular attention to the process of creating such intangibles. In particular, the Europe 2020 agenda confirmed the previous Lisbon strategy's goal to make Europe more competitive through knowledge and technological change. Moreover, the high heterogeneity displayed by countries and regions with regards to their capacity to create knowledge and innovation, as well as their ability to exploit knowledge diffusion across the European region, is behind a particular focus on its territorial dimension. This focus extends beyond borders, since European Neighbouring Countries (ENCs) suffer from relatively poor economic performance, mainly due to a severe technological gap in comparison to the European Union.

Our main aim is, consequently, to provide an overview of neighbouring countries' innovation inputs and outputs, to assess their orientation towards the EU for 'accessible knowledge', and their ability to combine these internal and external inputs in order to create knowledge. We describe, for the first time, national innovative activity in order to draw up a comprehensive picture of the European Knowledge Neighbourhood. We analyse both input (expenditure on R&D and education) and output indicators (patent applications and publications) for the 16 ENCs. Comparisons are made with the EU distinguishing the 15 old EU member states (EU15) from the 12 new member states (NMS12). Particular attention is also paid to studying the different channels of knowledge flows based on a comprehensive descriptive analysis of different indicators, each shedding light upon a specific aspect of scientific and technological relationships between the EU and ENCs.

Furthermore, we analyse the role of the main factors influencing the innovation process by means of the non-parametric method of Data Envelopment Analysis (DEA) to investigate the role of knowledge production function on the country level. While regression models are particularly suited to measuring the central tendencies of a given phenomenon, DEA is more appropriate for benchmarking analyses, as it enables the best performing units within a given set of entities to be identified. The DEA approach allows us to single out the specific characteristics of each region and to determine how far, in relative terms, they are from the most efficient areas. DEA can also be particularly useful for measuring efficiency in knowledge production without requiring specific assumptions on the behaviour of national innovation systems. DEA was firstly proposed by Farrell (1957) and was originally mainly used, like other frontier models, in productivity analysis at the micro-level. Recently, it has become increasingly popular at the macro-level as a non-parametric alternative to parametric estimation. Application of the DEA to the study of innovation performance is still fairly rare. Nonetheless analogous knowledge production function (KPF) models have been implemented in some studies investigating knowledge production at the national level, such as Guan and Chen (2012), Sharma and Thomas (2008), Wang (2007), and Wang and Huang (2007), who recently developed the pioneering contribution from Rousseau and Rousseau (1998). In our study, in contrast to most literature, we consider not only internal but also external inputs as potential determinants of the production of new knowledge and ideas. Results show that relative efficiency in knowledge production is extremely heterogeneous across countries. Some ENCs are fairly efficient in their ability to turn internal and external knowledge into innovation output, pointing to an effective knowledge potential in these countries.

The paper is structured as follows: based on a review of the empirical literature, the following section lays out the empirical strategy and discusses data issues. The subsequent two sections propose a descriptive analysis of innovative activity and knowledge flows, respectively, in order to understand the main features of the background scenario for our empirical analysis. The next section presents the empirical exercise based on Data Envelopment Analysis (DEA). In the final section, a synthesis based on the various indicators is developed, enabling us to give an overview of the European Knowledge Neighbourhood.

2. Analytical framework

2.1. Background literature

The KPF model pioneered by Griliches (1979) has long inspired scholars interested in the determinants of innovative activity at firm, country and regional level. The standard application of this model is to estimate a function where the innovative output, often measured by patenting activity, depends on a series of inputs. The most important input is R&D expenditure, usually combined with the level of human capital as an additional input. Knowledge inputs play a positive role in knowledge creation through three main mechanisms.

Firstly, in a similar way to the usual factors (labour and capital) involved the production function, knowledge inputs are recognised as the basic drivers behind knowledge production and innovation. The higher the knowledge investments made by an agent, the more likely they are to make discoveries and inventions. Furthermore, R&D and human capital investments are also required to turn those inventions into commercial innovations.

Secondly, beyond internal knowledge production processes, knowledge inputs and outputs generate externalities over time and space. Such knowledge flows occur when an idea generated by one particular economic agent is learned by other agents and this learning process creates the availability of what is called ‘accessible knowledge’ (Griliches 1992). This factor is essential if cases are to be considered where innovation is not solely the result of formal investment in research, but when it also derives from informal processes of learning-by-doing (Nelson and Winter, 1982) and/or from the absorption of external knowledge (Abreu et al., 2008).

Finally, knowledge inputs favour the creation of a knowledge absorption capacity. Indeed, the ability to understand, interpret and exploit external knowledge relies on prior experiences embodied in individual skills and, more generally, in an educated labour force (Engelbrecht, 2002; Archibugi and Filippetti, 2011). This absorption capacity is particularly studied in literature focusing on intentional knowledge flows, but it is also required for the absorption of non-intentional knowledge flows. In this regard, non-intentional knowledge flows can be promoted through intentional behaviours consisting of the creation of an absorptive capacity.

The interplay between these three mechanisms is considered to be at the root of economic growth in a knowledge-based economy. Romer (1990) was one of the first authors to highlight the role of technological change and human capital in explaining economic growth in an endogenous model. This original contribution was soon followed by Grossman and Helpman (1991), who emphasised the importance of knowledge flows across countries and the relevance of foreign innovation and knowledge on each country's productivity. Most importantly, the capacity to absorb knowledge and adopt technologies developed in other countries is essential for countries which lag behind the technological frontier. Such a capacity can indeed stimulate a catch-up process through the diffusion of innovations created in richer countries, as suggested by the technology gap theory by Abramovitz (1986) and Verspagen (1991).

Among the main factors which facilitate these transmissions, economists and geographers have stressed the importance of geographical closeness to help knowledge transfer between actors (Audretsch & Feldman 1996; Breschi & Lissoni 2001).Tacit knowledge may be more easily exchanged when face-to-face contacts are facilitated. Within this theoretical scenario, it is clear that European countries and their neighbours may be an excellent illustration of knowledge exchange between more advanced and relatively less developed countries, thanks to their geographical proximity. Our study will thus provide empirical evidence on the knowledge potential of neighbouring countries and on the ability of the EU and ENCs to exchange knowledge.

The literature has identified two main channels for the intentional diffusion of knowledge, both relying on interpersonal relationships. The most widespread idea is that the most important vector of knowledge diffusion relies on face-to-face interactions, particularly when knowledge has a significant tacit component. These interpersonal relationships would, in particular, be favoured by labour mobility on the one hand, and by a collaboration network on the other. The higher labour mobility is and the closer collaborative links between individuals are, the greater the probability of knowledge flows (Singh 2005). According to Zucker, Darby and Armstrong (1994) and Almeida and Kogut (1999), ideas are embodied into people and travel with them. Labour mobility would therefore enhance knowledge diffusion. Some recent studies confirm the positive role played by labour mobility on knowledge diffusion and knowledge accumulation (Agrawal, Cockburn & McHale 2006, Miguélez & Moreno 2012). Two main distinct frameworks have been used to investigate the role played by collaborations in knowledge diffusion. The former relies on patent citations (Singh 2005, Sorenson *et al*. 2006, Gomes-Casseres *et al*. 2006, and Agrawal *et al*., 2008) while in more recent studies, several authors rely on collaboration models. The dependent variable is, in this case, the probability of two agents collaborating, or the intensity of their collaboration, using either individual (Autant-Bernard *et al*. 2007, Frachisse 2011, Usai *et al*. 2013) or regionally aggregated data (Ponds *et al*. 2007, Scherngell & Barber, 2009). The results demonstrate that the ability to create ties depends on several factors: geographical distance but also technological, cultural, social and institutional proximity.

From this perspective, despite spatial proximity, technological, cultural and institutional aspects[i]may prevent knowledge exchanges in the European area and surrounding countries. We could therefore expect a large level of heterogeneity in the ability of European and neighbouring countries to exchange knowledge. Due to their shared history, some European countries may be closer to certain ENCs than others. By considering different channels of knowledge transmission, our study will provide insights into the underlying mechanisms.

2.2. Empirical strategy

In order to shed light on the European Knowledge Neighbourhood, our empirical strategy adopts two main approaches. The first is to gather various indicators of knowledge production and diffusion in order to characterise the main feature of the ENCs.

As detailed below, knowledge production is measured by patent applications and publications, whilst the main inputs are investments in R&D and education. These measures represent the standard set of statistical indicators designed to illustrate the structure of science, technology and innovation at country level. However, they have not yet been presented for ENCs, rendering the following descriptive analysis an original attempt to draw up a comprehensive and comparative picture of their innovative efforts and achievements.

In order to evaluate the intensity and mechanisms of knowledge diffusion between the EU and ENCs, we not only account for the level of knowledge production, but also provide measures of knowledge exchange between the EU and ENCs. We rely on various indicators in order to capture different channels of knowledge diffusion. Some, such as patent citations, have already been used to proxy knowledge flows in other contexts, but other are less common, and their combination in a single study is, to our knowledge, quite unique. In this respect, we contribute to an overview of potential knowledge interactions between the EU and ENCs, as well as suggesting original ways to account for the different facets of knowledge diffusion.

The second approach suggested in this paper then makes use of the indicators introduced in the descriptive part in order to assess the efficiency of ENC and EU countries in how they use of their resources. Output indicators are used as measures of innovative performance, as explained by both internal and external inputs. Internal inputs are proxied by knowledge investment efforts in R&D and education, while the ability to benefit from external inputs is accounted for through our knowledge interaction measures. This allows us to assess whether, despite low technological and scientific potential, ENCs benefit from their orientation towards the EU for their access to external knowledge and successfully turn their sparse knowledge resources into knowledge creation and innovation.

In order to assess the impact of knowledge inputs and knowledge diffusion on innovation output, an important tenet of the empirical literature relies on estimating knowledge production functions. Maggioni and Uberti (2009), and Miguélez and Moreno (2011) include both research networks and inventor's mobility within the knowledge production function. Sebestyen and Varga (2012) also investigate the impact of interregional knowledge networks on knowledge outputs. At the firm level, studies on technological alliances also investigate the role played by interpersonal relationship and innovation performances (e.g. Pieters *et al*. 2009).

However, all these studies rely exclusively on parametric tools, while non-parametric tools have proved to be more appropriate for benchmarking analyses, i.e. identifying the best performing units without requiring specific assumptions about the production function. Furthermore, DEA is a more appropriate method for dealing with a relatively small but highly heterogeneous set of countries, as is the case in our analysis. Recently, the investigation of knowledge production at the national level has been proposed by Wang (2007), Wang and Huang (2007), Sharma and Thomas (2008) and, more recently, by Guan and Chen (2012), continuing the research avenue opened by the pioneering contribution from Rousseau and Rousseau (1998). They all use granted patents to measure output of the knowledge production process and, in some cases, also publications. In addition, some national analyses implement richer models in order to test some interesting additional hypotheses. One such example is that of Schmidt-Ehmcke and Zloczysti (2009), who differentiate between knowledge production across sectors and Cullmann *et al*. (2009) who distinguish the impact of private and public R&D and different institutional and regulatory frameworks.

It should be noted that the use of non-parametric methods is also implemented in the analysis of regional innovation systems' performance. Zabala-Iturriagagoitia *et al*. (2007) make use of DEA to try to assess European regional efficiency based on information provided by the European Innovation Scoreboard (EIS). Studies by Enflo and Hjertstrand (2009) and Filippetti and Peirache (2012) also make important contributions to the literature. Both studies use DEA to analyse the main reasons behind the differentiated dynamics of European regions in recent decades. Furthermore, Foddi and Usai (2013) make use of non-parametric methods to assess the degree of efficiency with which European regions use internal and external inputs for the production of new knowledge and ideas. Their results show that relative efficiency in knowledge production is extremely heterogeneous across regions.

Our contribution to this literature, based on non-parametric approaches, is therefore two-fold. For the first time, we apply these techniques to studying knowledge efficiency in European Neighbouring Countries. We also enlarge the non-parametric approaches suggested so far by adding, along with internal inputs, external inputs in order to account for the potential international flows of knowledge. This allows us to reach efficiency scores informing us of the ability of European Neighbouring Countries to combine these internal and external factors in order to create knowledge.

2.3. Data and indicators

Knowledge production

The most common proxy for innovation production activity is the number of patents which have been either applied for or granted in a certain country. Patent statistics have made rapid progress in recent years thanks to a continuing effort to improve their quality and availability. Nevertheless, it is difficult to obtain data for all national intellectual property offices with all possible breakdowns, especially in relatively less developed countries.[ii] Intellectual property data published in this paper are patent applications taken from the OECD and the World Intellectual Property Organization (WIPO) Statistics Data Center. The WIPO Statistics Data Center includes information on patent counts based on international filing date and country of residence of the first named applicant. This is the primary source of data on Azerbaijan, Libya and Syria, countries which are not included in the OECD patent database. Data on the Palestinian territories is the only data which is not available in either database. It should be noted, therefore, that the indicator obtained from WIPO is only imperfectly comparable with that obtained from the OECD database. In the latter, multiple applicants and inventors are taken into account by dividing patents into fractions according to their country of residence.[iii] Nonetheless, divergence between the two databases in term of per capita values is negligible.

The WIPO and the OECD databases allow us to use patent data from two main sources: the Patent Cooperation Treaty (PCT) and the European Patent Office (EPO). PCT patents can be thought of as an indicator of innovations which will potentially be extended to global markets, while EPO patents concern innovations which, potentially, have a smaller target, that of European countries.

We present patent data both by the applicant's and the inventor's country of residence. In most cases the applicant is an institution[iv] (a firm or a government body such as a university or a public laboratory), which is the legal owner of the patent at the time of application. Thus, counting patents according to the applicant's country of residence tends to measure the degree of control over patents by each country's residents. It reflects the innovativeness of firms in a given country, regardless of the location of their research facilities. In contrast, an inventor is always an individual, usually a researcher employed in the applicant firm. Since patent statistics by inventor captures the national location where the invention is introduced, it better reflects the technological innovativeness of researchers and laboratories located in a given country, regardless of ownership. Moreover, in order to measure inventive activity, patents are counted according to priority year, i.e. the first filing worldwide and, therefore, the closest date to introduction of the invention.

We are aware that there are several shortcomings of using patent indicators. For this reason, we complement information provided by patents on commercially oriented innovations with data on publications which are more scientific in nature. We thus distinguish between two main categories of knowledge output: commercial and scientific. Data on publications are obtained using the Pascal database (INIST-CNRS). This covers most international scientific journals and mentions all authors' affiliations, giving an ample and fairly accurate picture of the scientific activities of EU countries and ENCs in all fundamental subjects or research lines.

Finally, we refer to the stock of patents and publications from 2000 to 2008 in order to have a relatively long time period, since ENCs' innovative activity is somewhat sporadic. Population data are expressed in millions in order to control for divergence due to differences in country size.

Internal knowledge resources

In order to account for R&D and human capital investments, the two basic knowledge inputs acknowledged in the literature, we use public and private R&D expenditure and public education expenditure. The latter consists of current and capital public expenditure on education and includes government spending on educational institutions (both public and private), education administration, and subsidies for private entities (students/households and other private entities).

It should be pointed out that ENCs record incomplete statistics on these phenomena. Data are missing for several years and, as a result, the indicator cannot always cover the whole period. In order to overcome this limitation, the average amount of R&D and education expenditure over the 2000-2008 period is calculated. Data are expressed in Purchasing Power Parity and, in order to control for country size heterogeneity, data are expressed as a percentage of GDP as well.

External knowledge resources

Exploring the capacity to benefit from external knowledge resources requires data allowing us to account for collaboration and potential knowledge flows between the EU and ENCs. Obviously, no single measure[v] exists and data availability constraints are high. We therefore suggest the use of different variables, each shedding light upon a specific aspect of the scientific and technological relationships between the EU and ENCs. We propose original, exploratory evidence of the characteristics of ENC knowledge flows based on a statistical databank, patenting, R&D collaboration, and co-publications. The following three channels of knowledge flow will be investigated:

a) relationships between applicants and inventors
b) cooperation links due to partnerships in the inventive activity (co-inventorship)
c) cooperation links due to partnerships in the scientific research activity (co-authorship and EU Framework Programme cooperation)

First, we develop a synthetic measure of applicant(s) and inventor(s) relationships, combining the two main indicators of international cooperation: the percentage of patents owned by foreign residents and the percentage of patents invented abroad according to the place of residence of either the inventors or the applicant. Another interesting indicator that will be analysed is the percentage of patents invented by an ENC resident with at least one inventor from a different country. More precisely, for both measures we will consider the relationships between each ENC and the European Union (EU15 and NMS12), the United States, Japan, and other ENCs.

One way to account for intentional knowledge diffusion would also be to rely on co-authorship (Zucker, Darby, Armstrong 1994, McKelvey *et al*., 2003). In this vein, we use the R&D cooperation database, following several earlier studies (Gomes-Casseres, Hagedoorn & Jaffe 2006). This last database comes from CORDIS and has been processed by the French Ministry of Research. It records participation in Framework Programme (FP) projects. Although the FPs are a European policy tool targeted mainly at EU countries, they also welcome non-EU partners. In this respect, it provides interesting information on the connectedness of ENCs to the European Research Area.

Based on these data, we first provide an overview of knowledge production in the ENCs. We then look at the intensity of knowledge diffusion between the EU and ENCs. Both types of indicators are then used to assess the efficiency of the innovation processes in the ENCs.

3. Knowledge production in European Neighbouring Countries

The analysis of patenting activity at country level in Table 1 points to three main stylised facts. First, patenting activity in ENCs is very low, except in Israel. Israel, with respectively 168 and 250 EPO and PTC patents per million inhabitants, is a clear outlier with a performance which is even higher than the average EU15 country. It accounts for around 95% of ENC patents. With the exception of Israel, south ENCs patent less than eastern ones, indicating a different technological potential in these groups of ENCs. Even within each group some noticeable differences arise. Within the eastern group, Belarus performs best while Azerbaijan lags behind. In the south ENCs group, Jordan leads, whereas in Algeria, Syria and Lybia, patenting activity is a very rare phenomenon.[vi]

Secondly, in spite of a higher propensity to file PCT patents, the above-mentioned results hold for PCT as well as EPO patents. It is however worth noting that the EPO orientation is stronger for south ENCs, and particularly for Jordan, which records 1.72 EPO patents per million inhabitants, the highest number of EPO patents per capita after Israel.

Thirdly, all these facts hold for data on both inventors and applicants, even though the number of patents by inventor's country of residence is significantly higher than by applicant's residence. This is what usually occurs in the case of small or less innovative countries, reflecting the higher level of internationalisation of their research activities with foreign ownership of domestic inventions.

Finally, as stated before, we use scientific publication as a direct measure of knowledge production. Israel is again at the top with more than seven hundred publications per million inhabitants; this implies more than 43,000 publications over the period. Excluding Tunisia, all other ENCs are below one hundred, with average values around 20 and 30 publications per million inhabitants. Slightly higher values are reached by Lebanon and Jordan with 75 and 69 publications. Syria, Libya and Azerbaijan are particularly worth noting for their poor performance in the creation of scientific knowledge; they report respectively only 4, 7 and 8 scientific publications per million inhabitants.

Turning to the main internal inputs of the knowledge production process, Table 2 shows that the southern group has an average R&D expenditure over GDP rate of 1%, while the eastern group reaches approximately 0.80%. However, it must be taken into account that the slightly higher average for southern ENC is again biased by Israel, which reaches the exceptional average of 4.50% of GDP in the period between 2000 and 2008. This average is much higher than the same index for EU15 or for the OECD countries as a whole. Excluding Israel, the south group's average falls drastically to 0.35%.[vii]

The second input indicator presented is public spending on education. As can be seen from the last column of Table 2, Moldova (6.68%), Tunisia (6.38%), and Israel (6.34%) record the highest values, above the EU15 average. The lowest value is registered for Lebanon, Georgia, Armenia and Azerbaijan with a share of education expenditure over GDP of only 2%. The remaining countries are in line with the NMS12 average, i.e. above 4%.

The technological and scientific potential of ENCs is therefore low but far from negligible. On average, they are sometimes almost comparable to NMS in terms of resources devoted to knowledge creation. This result is, however, mainly driven by Israel's performance, which exceeds most EU15 countries. Among the other ENCs, Belarus, Ukraine and Tunisia exhibit the highest potential. Studying how EU countries may contribute to and benefit from the development of a positive dynamics of research and innovation in ENC is thus an important issue. In order to shed some light on this point, the next section describes scientific and technological relationships between the EU and ENCs.

4. Knowledge flows across the European Union and European Neighbouring Countries

Based on the collaboration indicators described in Section 2, this section investigates the extent to which ENCs are oriented towards the EU for their knowledge exchanges.[viii] Figure 1 focuses on foreign ownership of domestic inventions in neighbouring countries and, conversely, ENC domestic ownership of foreign inventions.

Figure 1 about here

It shows the very unbalanced structure of patent ownership and patent inventorship. Except for Jordan, all ENCs face a drastic disequilibrium between the share of their local inventions owned by foreign applicants (more than 30% in most cases) and the share of the foreign inventions own locally (less than 20% in most cases). This is not very surprising as it probably follows the pattern of Foreign Direct Investment.

Figure 1 also highlights some interesting specificities in terms of the internationalisation of technological activities. Armenia, Tunisia and Morocco and, to a lesser extent, Lebanon and Algeria are the most EU-integrated countries regarding patent activities. For Morocco, Tunisia and Lebanon, this patent ownership structure is coupled with a significant number of patents (illustrated by the size of the bubble), meaning that significant knowledge flows could result from these patent ownership interactions. For Armenia and Algeria however, very few patents are recorded, showing the difficulty of such patent ownership interaction leading to systematic knowledge flows.

This calls for additional analysis. The ability of this potential knowledge exchange to contribute to local knowledge output will be explored in section five, using the DEA analysis.

Our second set of indicators relies on co-inventorship and points to a higher EU orientation for southern ENCs (excluding Israel) than for eastern ENCs. As shown in Figure 2, the propensity to co-patent abroad depends on the level of technological potential. More innovative countries such as Israel are characterised by a lower share of international co-inventions.

Figure 2 about here

In addition, the majority of neighbouring countries are Europe-oriented in patent cooperation. More than one international co-invention out of two in ENCs involve a European inventor. Noticeable exceptions are Israel, Ukraine and Georgia. The weak EU orientation of these countries is all the more remarkable in that they are also the countries with higher numbers of co-inventions. The disparity between these three countries is, however, quite high as far as relative levels of co-inventions are concerned. Israel displays a small share of international co-inventions (16%) while Ukraine and Georgia are more internationally oriented (respectively 58% and 83% of co-inventions involve foreign partners). This feature is shared by all other ENCs, and reflects the weak internal capacities of these countries. They need to find their partners abroad, due relatively lower levels of local opportunities. As such, EU countries may play a critical role in the technological development of ENCs.

The role that co-inventorship may play in ENCs' innovation capacity is investigated in the DEA analysis.

Moving to scientific indicators (co-publication and FP collaborations), a more balanced orientation emerges for most ENCs. Different profiles of neighbouring countries in terms of propensity to co-publish abroad can be identified, together with a relatively high European orientation in co-publication practices for a majority of neighbouring countries. Compared to co-inventorship, Figure 3 shows that co-authorship is a slightly less important aspect of technological processes in ENCs. The share of international co-publication is, in most cases, lower than the share of international co-inventorship reported in Figure 2, especially for southern ENCs. Israel is, once again, a noticeable exception. Analysis of the propensity to co-publish with foreign partners (international co-publication) compared to the propensity to co-publish with authors located in the same country (internal co-publication) allows us to distinguish different groups within the neighbouring countries.

Figure 3 about here

On the whole, three main groups of countries can be identified. The first brings together Tunisia, Morocco and Algeria. These three countries are the most intensively oriented towards the EU for their scientific activities. They are strongly involved into FP projects and their share of co-publication with EU countries exceeds 80%. Within this group, Tunisia has a specific profile given its level of scientific potential (see Section 3, Table 1). The intensity of knowledge flows between the EU and Tunisia is therefore very high.

The second group gathers all eastern ENCs, except Azerbaijan. These countries exhibit a high propensity to co-publish with international partners (more than 50%) together with a high propensity to choose EU partners (also more than 50%).

Israel, Jordan and Egypt belong to the third group. Their common features are reliance upon a lower level of co-authorship and a relatively low orientation towards the EU. This results from the stronger scientific links they have with the US compared to other ENCs (Autant-Bernard and Chalaye 2012). Due to the dynamism of these three countries in terms of publications as well as FP participation, one could expect higher integration with the EU. Israel in particular records a participation density in FP6 similar to European countries. In terms of FP participation, Tunisia, Morocco and Algeria also perform well, confirming their European orientation. In this regard, these countries may provide interesting opportunities for new co-publications with EU countries.

It is worth noticing that Armenia, Belarus and Moldova, which have a fairly strong orientation towards Europe, both in terms of scientific and technological cooperation, nonetheless record however low participation density in FP. There may, therefore, be room for improving R&D collaborations between the EU and these countries.

Once again, the impact of EU collaboration on countries' knowledge output is studied in the DEA exercise, the number of FP participations being introduced as a proxy for embeddedness within EU knowledge networks.

5. Knowledge production efficiency

5.1. DEA Methodology

DEA is a methodology to measure the efficiency of a set of decision-making units (DMUs) which proves particularly useful when the production process presents a structure of multiple inputs and outputs.

DEA uses data on inputs and outputs to search either for the points with the lowest input intake for any given output (input-oriented DEA) or the highest output performance for any given input (output-oriented DEA). The points obtained are then connected to form the efficiency frontier, consisting of the best performing units, which envelops all the other less efficient units.

One of the main advantages of DEA is that it does not require the selection of a specific functional form for the relation linking inputs to outputs. DEA is also particularly informative because one can specifically identify and quantify the efficiency gap and its sources for each evaluated unit. However, this technique has also some drawbacks which have to be borne in mind. First, the inclusion/exclusion of inputs can significantly affect results. Secondly, the number of efficient firms on the frontier tends to increase with the number of input and output variables. Finally, we have to be aware that the estimated frontier is only defined relative to the best-practice observations in the sample and it, thus, ignores the potential existence of more efficient cases outside the sample data.

In the following exercise we address some of these problems. In particular, we choose the smallest set of inputs using a preparatory study based on the econometric estimation of a production function.[ix] We then replicate the econometric analysis and corresponding DEA for each output rather than using the multiple output setting, which would make the number of efficient units too large. Following Cullinane *et al*. (2005), we then use the output-oriented approach,[x] since we believe that economic agents and policy makers in each country aim at reaching long term increases in the national innovative capacity, so as to improve their competitiveness. Finally, DEA takes into consideration returns to scale in calculating efficiency, allowing for the concept of increasing or decreasing efficiency based on size and output levels. We exclude the assumption of constant return to scale (CRS), which would require that each unit operates at its optimal scale. In contrast, we employ the variable return to scale (VRS) model, developed by Banker *et al*. (1984), which is more realistic in a context of imperfect competition, financial constraints and other potential market failures.

In this study we use the output oriented DEA firstly proposed by Farrell (1957):

$$\mathrm{TE}(\mathrm{inn_i}, \mathrm{inputs_i}) = \max\{\theta\colon (\mathrm{inn_i}, \theta\mathrm{inputs_i}) \in \Psi\}$$

Where θ measures the radial distance between the observation and the efficiency frontier. The efficiency score is the point on the frontier characterised by the level of inputs that can be reached if the DMU is efficient (Simar & Wilson 1998). A value of $\theta = 1$ indicates that a country is fully efficient and thus is located on the frontier based on the technology set ψ, which is unobserved and is, thus, estimated using the DEA.

In light of the theoretical and empirical literature on the estimation of knowledge production functions conveyed in Section 2, we assume that the production of new ideas is the result of internal and external factors. As already emphasised above, the output variable which proxies the creation of commercial knowledge is given by the amount of patent activity (at EPO or PCT) either related to the inventors' or the applicants' country of residence. The other measure of innovative performance refers to scientific knowledge production and is given by the number of scientific publications. As far as the main internal inputs of the knowledge production process are concerned, the preliminary analysis (reported in Table A1 in the Appendix) suggests that investment in R&D is essential for commercial knowledge, whilst public expenditure in human capital formation is crucial for the creation of scientific knowledge. Moreover, again based on the preliminary econometric analysis, external knowledge sources are beneficial to knowledge production.[xi] In particular, results suggest that the inventive collaborations (proxied by co-inventorships) can prove useful complementary inputs to produce patents relating to the inventors' country of residence; on the contrary, inventor-firm relationships (proxied by applicant-inventor networks) are an essential input to produce patents referring to the applicants' country of residence. Finally, FP6 partnerships are suggested as the main input for scientific publications, since it is the only significant explanatory variable in the corresponding econometric analysis. Moreover, since we aim to analyse the creation and diffusion of knowledge among EU countries and ENCs, we consider only knowledge flows between these countries. Finally, in all models, the country's population size is included in order to control for differences in the magnitude of each economic system.

The combinations identified and described above result in five different models for DEA application, four models relate to commercial knowledge and one to scientific knowledge. These output-inputs combinations are summarised in Table 3.

Table 3 about here

5.2 Findings

The sample used for the DEA includes 37 of all 40 EU countries and ENCs for the period from 2000 until 2008. Four countries are excluded, namely Algeria, Lebanon, Libya and Syria, because either data are missing or the phenomenon is negligible. Nonetheless, the DEA exercise still represents an original contribution to the existing literature because of the wide heterogeneity of the set of countries under examination.[xii] Such countries are different not only in knowledge production but also in many other economic, social and cultural dimensions.

As previously mentioned, each of our DEA models for evaluating inter-country innovation efficiency includes one output and three inputs. Since we adopt an output-oriented model, we are implicitly assuming that countries aim to maximise innovative activity resulting from their inputs. Summary statistics on relative scores (ranging from a minimum of zero to a maximum of one) for the five different models are presented in Table 4 (more details can be found in the Appendix). We provide some averages for three main groups of countries: EU15, which refers to the 15 Member States of the European Union as of December 2003, before EU main enlargement; NMS12 which stands for the twelve new member states which entered the EU in 2004 and in 2006; and the ENCs.

Table 4 about here

As expected, results are quite different with respect to the three groups. EU15 countries are significantly more efficient than the other two groups, even though we observe that ENCs are always above NMS12. This is mainly due to the fact that some ENCs are identified as demonstrating best practice at low input levels whilst most NMS12 have EU15 as their respective benchmarks. It should be, therefore, emphasised that those ENCs which are identified as efficient are positioned in the left hand side of the knowledge production function, with low input levels and, consequently, low output levels. In other words, efficiency does not necessarily correspond to high innovative performance. Moreover, results reported in the lower part of Table 4 show that a substantial number of countries are on the frontier, as in similar analyses with a relatively low number of countries (see Wang and

Huang 2007 and Wang 2007, for OECD countries). Most importantly, the number of efficient countries does not vary significantly from one model to the other, ranging from 8 in model 1 to 11 in model 3. Table 4 also shows that intermediate efficiency scores (those from 0.6 to 0.8) are quite rare, while most countries have an efficiency score below 0.6. The distribution of efficiency score is more homogenous in the last model, concerning the production of scientific knowledge. In this latter case the number of countries with an efficiency score over 0.8 is exactly equal to the number below 0.6.

Tables 5 and 6 provide further information on the results of our DEA exercise. Table 5 identifies the countries which are on the frontier (efficiency score equal to one) while Table 6 indicates the countries which are the least efficient (efficiency score below 0.2 for commercial output and below 0.4 for scientific knowledge).

Table 5 about here

Table 5 shows that there are five countries which are efficient in all five models: Luxemburg among EU15, Malta among NMS12 and Armenia, Georgia and Israel among the ENCs. Excluding Israel, the most efficient countries are very small and have a very particular profile. Besides their limited knowledge production in absolute terms, Armenia and Georgia have a very high knowledge productivity in terms of patents per R&D and per external inputs, especially compared to the other ENCs.

Two main facts could explain this good performance. The first one lies in the notion of frugal innovation (Zeschky, Widenmayer and Oliver, 2011). Such resource-constrained innovations, mainly produced by local corporations in emerging countries, provide simpler and cheaper solutions compared to existing products from developed countries. The development of this type of innovations may induce a relatively high capacity of innovation in spite of low R&D and education resources (see for instance the Romanian tablet case studied by Popescu, 2013). Since our efficiency scores are not relevant tools to explore this issue, and given that most empirical evidence has come from Asia so far, further research based on ENCs case studies would be requested.

The second explanation refers to knowledge diffusion. It is worth remembering that the descriptive analysis above has shown that Georgia and Armenia are countries with a fairly weak R&D and education sub-system[xiii] but are quite inclined to cooperate, although the former is mostly US-oriented while the latter is more EU-oriented. In other words, these countries apparently manage to integrate low internal resources with the absorption of external knowledge i.e. these countries are able to exploit the public nature of knowledge in the early stages of their technological path. This possibility is, obviously, less available as countries get closer to the technological frontrunners, as is the case of most NMS. As a matter of fact, none among the NMS, with the exception of the distinctive cases of Malta and Cyprus, appear on the list of the most efficient countries in commercial and scientific production. This result suggests that these countries are developing their industrial and technological base along the lines of EU15 countries. However, knowledge coming from this group of countries is not easily accessible. On the contrary, ENCs have a very basic national innovation system and the benchmark countries are within the same ENC group, even though they can obtain basic knowledge from advanced countries. Using this line of reasoning, it is interesting to note the case of another small highly cooperative country, Moldova, which manages to stay on the frontier of the production function, albeit for EPO patents only.

As far as EU15 countries are concerned, Germany is efficient in four of the five models, i.e. in the production of commercial knowledge. Sweden is another interesting case, since it is efficient in four of the five cases with the exclusion of EPO patents referring to inventors' residence. Other advanced industrial countries, such as Finland and the Netherlands, are also often on the frontier in patent production.

Table 6 presents the least technically efficient countries, among which we find several ENCs. In particular, Egypt, Tunisia and Morocco, are always inefficient whatever measure of output is adopted. This result is not surprising, given the very low patent productivity in term of R&D and knowledge flows. Nonetheless, it is worth emphasising that these countries, despite growing awareness of the importance of technology and science policies (see ESTIME project and Arvanides 2013), are still unable to use their scarce, but growing, resources devoted to innovation effectively. Moreover, these countries do not exploit the potential knowledge flow which is generated as a result of their relative openness to international cooperation. A similar interpretation applies to Ukraine and Belarus, which are among the inefficient set for the production of EPO patents only. This is probably due to the fact that their innovations are more internationally-oriented and are, therefore, most often patented at PCT rather EPO.

As far as EU15 and NMS countries are concerned, Table 6 shows that several transition economies, especially Romania and Bulgaria, are inefficient. Nonetheless, it is clear that in this case, results are less stable since no single country appears in the least efficient set in all rankings. Finally, the only EU15 country which appears in the list of the least efficient countries is Portugal, but only when PCT patents are considered as knowledge output.

Table 6 about here

In conclusion, results derived from this empirical exercise are quite interesting since they reveal some unexpected outcomes. Many ENCs are on the technological frontier and thus are using their scarce resources efficiently. However, it must be stressed that they 'lie' on the frontier with low accumulated factors and therefore very low levels of innovation, in other words, they are very close to the edge of the frontier. This implies that these countries are particularly favourable to the absorption of external knowledge. Nonetheless, we have also observed that other countries, despite being well orientated towards cooperation, have proved less effective in channelling external knowledge to their knowledge production system.

All in all, the DEA analysis shows that there is a fairly large spectrum of technological profiles and patterns among ENCs. Nonetheless, it is clear that the external channel can be a substantial input to complement and integrate scarce internal resources. Consequently, developing knowledge exchanges between the EU and ENCs is still a crucial tool to improving their innovative capacity as well as that of the area as a whole.

6. Synthesis and main policy implications

Through the use of a variety of information and data, this paper attempts to illustrate the main features of European Neighbouring Countries in terms of their capacity to produce knowledge and to exchange ideas with the European Union and the rest of the world. Results of the descriptive analysis and the non-parametric estimates are summarised in Table 7 and offer a fairly diverse picture with various innovative capability and performance profiles among ENCs.

One very distinctive case is Israel: it records very high scientific and technological capabilities as well as a high level of efficiency despite the fact that there is a relatively modest connection with the EU for knowledge exchange, with the remarkable exception of FP partnerships. Geographical and cultural proximity seem to offer a platform for mutual gains from the exchange of knowledge and co-creation of new ideas which remains somewhat dormant.

Among the other ENCs, a general pervasive weakness in terms of scientific and technological capacity can be identified, which is the result of low levels of investment in R&D and education in quantitative and qualitative terms. Nonetheless, DEA has identified several countries which have been able to successfully convert their rare resources into commercial inventions and new scientific knowledge. This is particularly the case for Armenia, Georgia and, to a lesser extent, Belarus and Moldova. These countries seem to be able to take full advantage of their connections with technologically advanced countries.

Among southern neighbouring countries, a general higher awareness of the importance of technological progress and a fairly high cooperative attitude towards the EU can be observed. However, there are several inefficient countries, namely Tunisia, Egypt and Morocco. All in all, it is clear that the relationship between the EU and ENCs, which is often dictated by historical and cultural reasons, does not necessarily reflect higher ENC technological and scientific performance. Indeed, the analysis also reveals the differentiated role played by the various knowledge diffusion channels. Technological and scientific collaborations, measured through co-inventorship and co-authorship, often build upon historical and cultural linkages and are favoured by common languages and proximity. As for patent ownership, the geographical and linguistic dimensions play a lesser role: Europe is therefore less pivotal and the US emerges with a more central role.

On the whole, whatever the channel, one of the most striking facts is that knowledge diffusion remains weakly developed between the EU and ENCs. Given their public and private research potential on the one hand and higher physical proximity than the US on the other, there are large cooperation opportunities for neighbouring countries. Conversely, efficiency scores point out that even if most ENCs continue to rely on low knowledge inputs, some nonetheless use them efficiently. This underlines the existence of innovative skills and potential in these countries. EU innovation policies oriented towards the ENCs could therefore be more oriented towards the creation of a real neighbouring knowledge space in which ideas and know-how flow between the EU and its neighbours. Due to the weak knowledge resources in most ENCs, not only would channels for knowledge diffusion need to be enhanced, but these countries would also need help to improve their absorptive capacities.

In conclusion, it is necessary to emphasise that this study is exploratory in nature and calls for further research efforts in several directions. First of all, data availability remains limited and restricts researchers to a narrow view of knowledge production and diffusion in the European neighbourhood. Our output indicators point largely to innovations carried out in the industrial sector and neglect most innovations in services. Furthermore, focusing on patent and scientific publications, we mainly observe technological innovation, while in developing countries, non-technological improvements, such as organisational or social innovations, may be equally, or more, important. Moreover, our input indicators may capture only part of the factors required for innovation: i.e. the more tangible ones, for which indicators are available. In that case, the estimated efficiency scores may be biased since, in some contexts, R&D inputs are more crucial than in others. In other words, in ENCs, other intangible factors, related for example to the institutional context, may be particularly important and need to be taken into account.

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Table 1: Commercial and scientific knowledge production, country average 2000-2008

country	Commercial knowledge: inventor(s) EPO per million pop	Commercial knowledge: inventor(s) PCT per million pop	Commercial knowledge: applicant(s) EPO per million pop	Commercial knowledge: applicant(s) PCT per million pop	Scientific knowledge: Publications per million pop
Armenia	0.37	2.18	0.11	1.90	34.69
Azerbaijan	0.12	-	0.08	0.57	8.28
Belarus	0.69	1.96	0.42	1.50	38.76
Georgia	0.52	1.81	0.17	1.29	29.38
Moldova	0.43	1.19	0.31	0.94	19.42
Ukraine	0.54	1.80	0.25	1.44	29.46
ENC-East	**0.50**	**1.81**	**0.24**	**1.34**	**28.08**
Algeria	0.03	0.20	0.01	0.18	18.33
Egypt	0.12	0.46	0.07	0.39	21.30
Israel	167.94	248.91	135.35	208.11	712.00
Jordan	1.72	1.18	1.42	0.64	69.32
Lebanon	0.99	1.14	0.36	0.45	75.73
Libya	0.05	-	0.04	0.02	7.02
Morocco	0.18	0.41	0.10	0.33	31.79
Syria	0.05	-	0.02	0.16	4.61
Tunisia	0.36	0.58	0.28	0.51	124.42
ENC-South	**6.36**	**10.93**	**5.09**	**7.97**	**53.94**
ENC-South (without Israel)	**0.18**	**0.39**	**0.11**	**0.30**	**28.80**
EU15	**139.89**	**109.90**	**136.48**	**109.16**	**513.76**
NMS12	**5.81**	**6.98**	**4.48**	**5.83**	**134.79**

Source: CRENoS calculation on OECD data. EPO data for AZ, LY, SY: calculation on WIPO data

Table 2: R&D and education expenditure, country average 2000-2008

country	R&D exp PPP 2005, million $	R&D expenditure (% GDP)	Education exp PPP 2005, million $	Education exp (% GDP)
Armenia	25.39	0.22	313.96	2.70
Azerbaijan	88.19	0.23	1,109.44	2.89
Belarus	566.05	0.71	4,716.71	5.96
Georgia	27.76	0.21	385.49	2.57
Moldova	37.38	0.43	527.12	6.68
Ukraine	2,461.82	0.99	11,571.41	4.66
ENC-East	**3,206.58**	**0.80**	**18,624.13**	**4.65**
Algeria	421.02	0.20	11,001.00	4.97
Egypt	865.71	0.25	14,947.90	4.53
Israel	7,192.88	4.50	10,135.55	6.34
Jordan	94.50	0.39	-	-
Lebanon	-	-	937.87	2.48
Libya	-	-	-	-
Morocco	624.72	0.62	4,487.07	4.27
Syria	-	-	4,209.99	5.75
Tunisia	614.81	0.88	4,461.79	6.38
ENC-South	**9,813.63**	**1.07**	**50,181.18**	**4.58**
ENC-South (without Israel)	**2,620.76**	**0.35**	**40,045.63**	**4.28**
EU15	**219,894.42**	**1.89**	**587,768.50**	**5.06**
NMS12	**10,417.34**	**0.74**	**66,412.39**	**4.72**

Source: CRENoS calculation on World Bank Data

Table 3 DEA models: output and input indicators

Model		OUTPUT	INPUTS	
			Domestic investments	External knowledge flows
1	Commercial knowledge	EPO patents by applicants' residence	R&D expenditure	EPO applicant-inventors links
2		PCT patents by applicants' residence		PCT applicant-inventors links
3		EPO patents by inventors' residence		EPO co-inventorships
4		PCT patents by inventors' residence		PCT co-inventorships
5	Scientific knowledge	Scientific publications	Education expenditure	FP6 partnerships

Table 4: Summary statistics

	(1)	(2)	(3)	(4)	(5)
EU15	0.68	0.68	0.68	0.67	0.87
NMS12	0.37	0.41	0.38	0.42	0.55
ENC	0.49	0.48	0.54	0.49	0.70
Mean	0.53	0.54	0.55	0.54	0.72
Std. Dev	0.36	0.32	0.36	0.33	0.26
N. efficient	8.00	9.00	11.00	10.00	10.00
Countries with efficiency score between 0.8 and 1	12.00	10.00	13.00	11.00	16.00
Countries with efficiency score between 0.6 and 0.8	4.00	4.00	2.00	4.00	4.00
Countries with efficiency score less than 0.6	21.00	23.00	22.00	22.00	16.00

Table 5: VRS technically efficient countries

	Commercial knowledge				Scientific knowledge
	inventors' residence		applicants' residence		Publications
	EPO	PCT	EPO	PCT	
EU15	Germany Luxembourg	Finland Germany Luxembourg Netherlands Sweden	Finland Germany Luxembourg Netherlands Sweden	Finland Germany Luxembourg Netherlands Sweden	Finland France Luxembourg Sweden United Kingdom
NMS12	Malta Cyprus	Malta	Malta Cyprus	Malta Cyprus	Malta
ENC	Armenia Georgia Moldova Israel	Armenia Georgia Israel	Armenia Georgia Moldova Israel	Armenia Georgia Israel	Armenia Belarus Georgia Israel

Table 6. VRS technically inefficient countries (less than 0.2/0.4)

	Commercial knowledge				Scientific knowledge
	inventors' residence		applicants' residence		Publications*
	EPO	PCT	EPO	PCT	
EU15		Portugal		Portugal	
NMS12	Bulgaria Czech Republic Slovak Republic	Lithuania Poland Romania	Bulgaria Hungary Slovak Republic Romania	Romania	Cyprus Lithuania Romania Latvia
ENC	Belarus Ukraine Egypt Tunisia Morocco	Morocco Tunisia	Belarus Egypt Ukraine Tunisia Morocco	Jordan Morocco Tunisia	Egypt

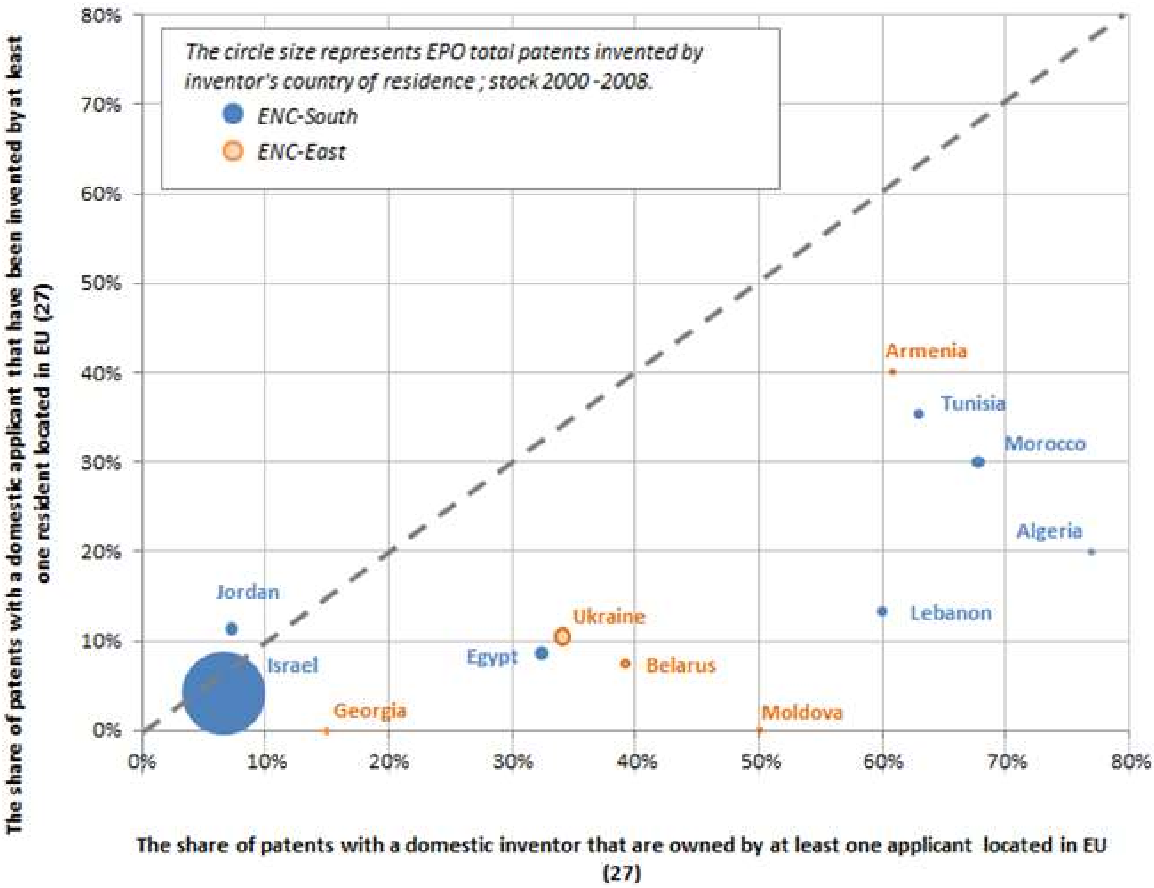
*Since there are not country with a VRS less than 0.2, we consider the threshold of 0.4

Table 7: Synthesis of ENC knowledge potential and involvement in knowledge exchanges with EU.

Country	Knowledge production		Knowledge resources	Knowledge exchanges (orientation towards the EU)				Efficiency
	Commercial knowledge	Scientific knowledge		Patent ownership	Co-inventorship	Co-authorship	FP participation	
Israel	++	++	++	--	-	-	++	++
Tunisia	-	+	-	++	++	++	+	--
Morocco	--	-	--	++	++	++	+	--
Armenia	-	-	--	++	++	+	--	++
Algeria	--	-	--	+	++	++	+	NA
Lebanon	-	+	--	+	++	+	-	NA
Belarus	-	-	-	-	+	+	-	+
Moldova	--	-	-	-	+	+	-	+
Ukraine	-	-	-	-	-	+	+	-
Egypt	--	-	--	-	+	-	+	-
Georgia	-	-	--	--	--	+	-	++
Jordan	-	+	--	--	NA	-	-	+
Syria	--	--	-	NA	NA	+	-	NA
Libya	--	--	NA	NA	NA	NA	-	NA
Azerbaijan	--	--	--	NA	NA	--	--	

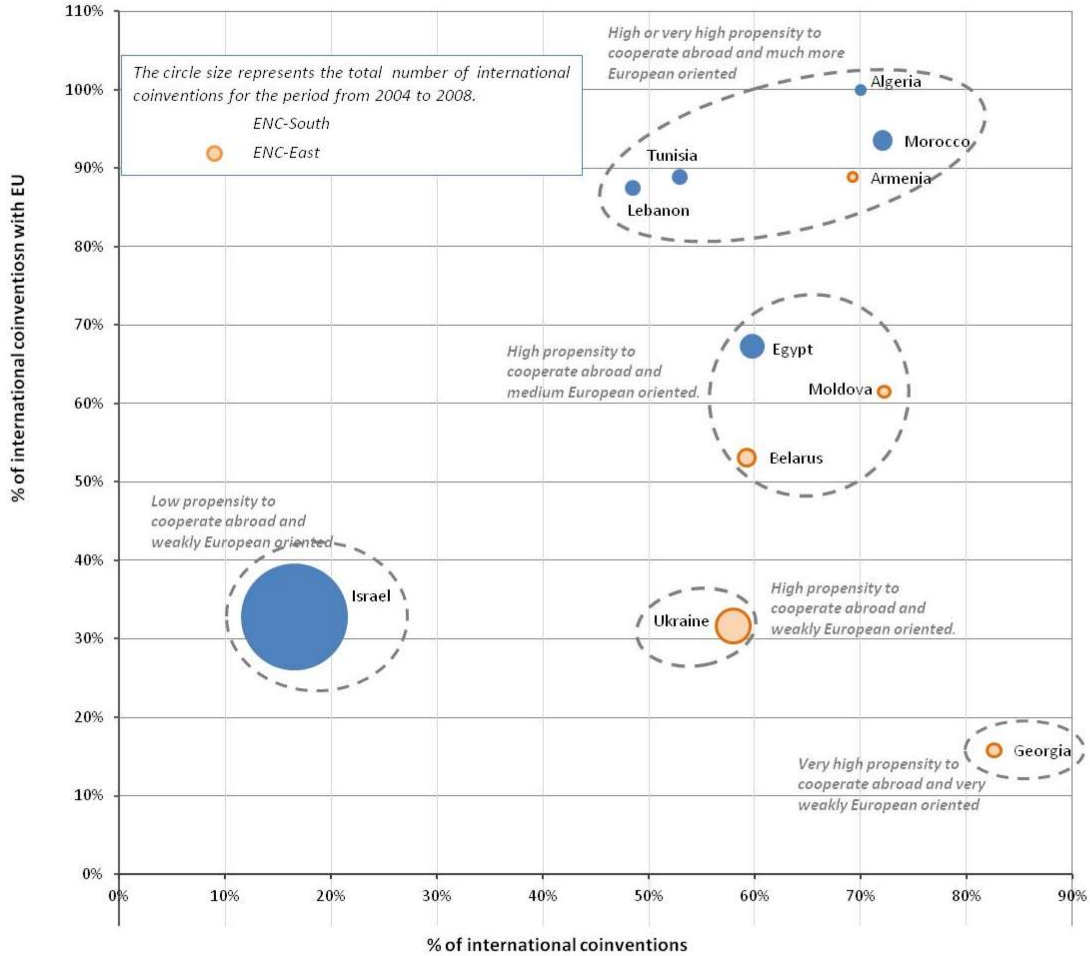
Source: Authors' own synthesis based on all previous indicators discussed in the paper

Figure 1. Share of ENC patents with EU inventors and ENC inventors involved in EU patents



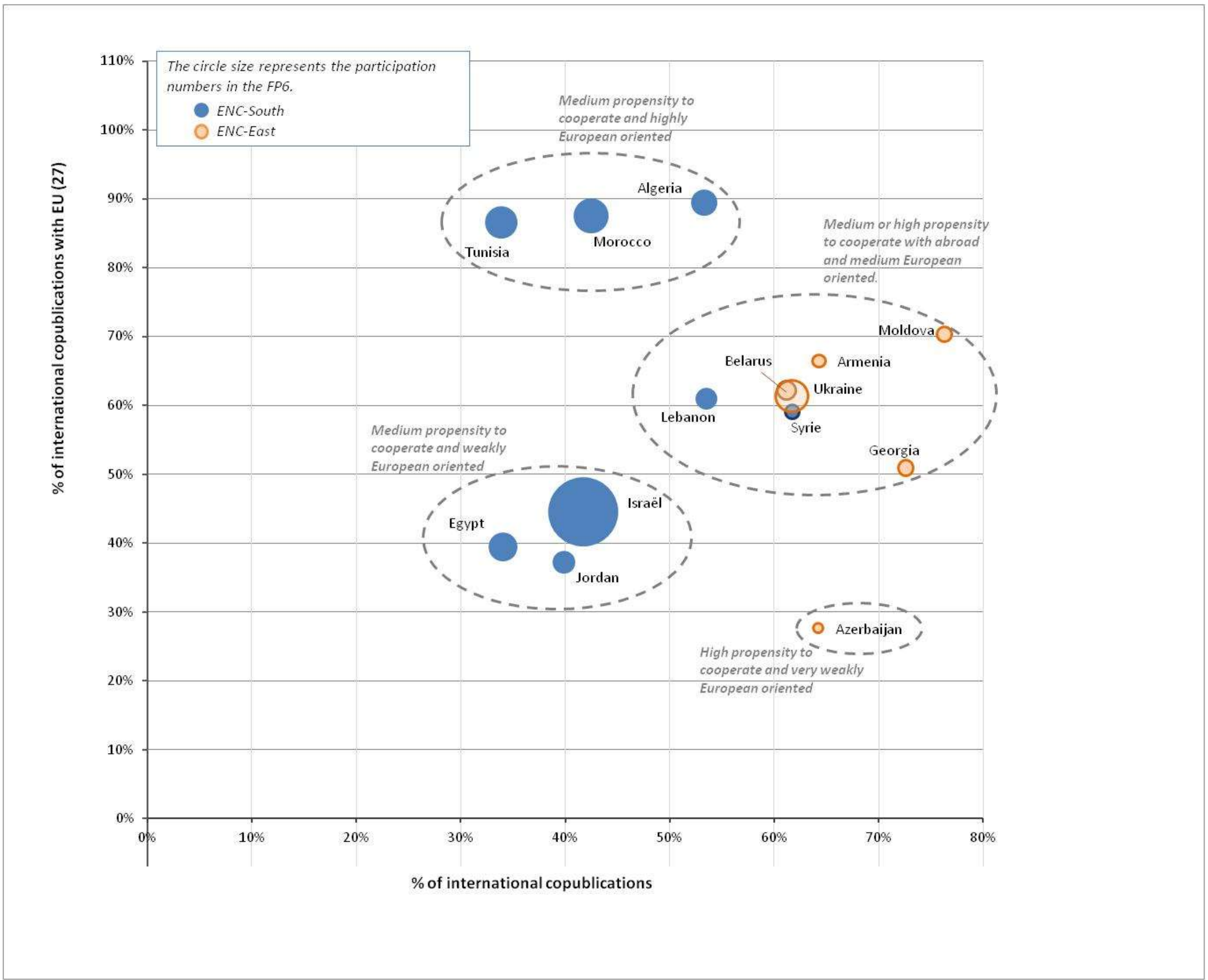
Source: EuroLIO calculation on OECD data

Figure 2. Share of co-invention patents in ENCs



Source: EuroLIO calculation on OECD data

Figure 3. Share of scientific co-authorship and FP participations in ENCs



Source: EuroLIO calculations based on the PASCAL database (INIST-CNRS) and FP database (French Ministry of Research).

Appendix

Table A1: Parametric method -OLS results

Dependent variable	**Publications (Ln)**		**PCT app (Ln)***		**PCT inv (Ln)***		**EPO app (Ln)***		**EPO inv (Ln)***	
Education expenditure (Ln)	1.194***	1.068***								
	(0.109)	(0.117)								
R&D expenditure (Ln)			1.346***	0.219*	1.260***	0.201	1.740***	0.366**	1.564***	0.323***
			(0.0970)	(0.120)	(0.104)	(0.126)	(0.0981)	(0.142)	(0.108)	(0.0989)
FP6 partnership (Ln)		0.151*								
		(0.0830)								
PCT app-inv links (Ln)				0.918***						
				(0.0941)						
PCT co-inventorships (Ln)						0.973***				
						(0.115)				
EPO app-inv links (Ln)								1.013***		
								(0.0850)		
EPO co-inventorships (Ln)										1.047***
										(0.0770)
Constant	0.490	0.280	7.940***	-0.199	4.487***	0.124	12.22***	2.401	8.045***	2.101
	(1.392)	(1.178)	(1.298)	(0.929)	(1.461)	(1.027)	(2.071)	(1.430)	(1.757)	(1.351)
Observations	36	36	38	38	38	38	38	38	38	38
R-squared	0.937	0.944	0.891	0.978	0.902	0.978	0.903	0.977	0.911	0.981

Note: population is included as a control

Robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1

* we are including total external flows links

Table A2: Efficiency scores ranking

Model 1		Model 2		Model 3		Model 4		Model 5	
country	**vrste**	**country**	**vrste**	**country**	**vrste**	**country**	**vrste**	**country**	**vrste**
Armenia	1.00	Armenia	1.00	Armenia	1.00	Armenia	1.00	Armenia	1.00
Georgia	1.00	Georgia	1.00	Georgia	1.00	Georgia	1.00	Belarus	1.00
Moldova	1.00	Israel	1.00	Moldova	1.00	Israel	1.00	Georgia	1.00
Israel	1.00	Finland	1.00	Israel	1.00	Finland	1.00	Israel	1.00
Germany	1.00	Germany	1.00	Finland	1.00	Germany	1.00	Finland	1.00
Luxembourg	1.00	Luxembourg	1.00	Germany	1.00	Luxembourg	1.00	France	1.00
Cyprus	1.00	Netherlands	1.00	Luxembourg	1.00	Netherlands	1.00	Luxembourg	1.00
Malta	1.00	Sweden	1.00	Netherlands	1.00	Sweden	1.00	Sweden	1.00
Italy	0.98	Malta	1.00	Sweden	1.00	Cyprus	1.00	United Kingdom	1.00
Netherlands	0.97	Denmark	0.86	Cyprus	1.00	Malta	1.00	Malta	1.00
Sweden	0.96	Cyprus	0.78	Malta	1.00	Denmark	0.83	Netherlands	0.99
Finland	0.94	United Kingdom	0.74	Italy	0.90	France	0.68	Estonia	0.98
Denmark	0.75	Italy	0.70	Jordan	0.90	Italy	0.68	Belgium	0.97
Austria	0.66	France	0.62	Denmark	0.72	Ireland	0.61	Greece	0.93
Belgium	0.64	Austria	0.56	France	0.66	United Kingdom	0.60	Denmark	0.92
France	0.62	Ireland	0.55	Ireland	0.54	Egypt	0.50	Germany	0.90
United Kingdom	0.57	Slovenia	0.51	Lithuania	0.53	Slovenia	0.46	Spain	0.78
Slovenia	0.47	Belgium	0.47	Austria	0.52	Spain	0.45	Slovenia	0.75
Ireland	0.41	Hungary	0.44	Belgium	0.51	Belgium	0.40	Italy	0.69
Jordan	0.36	Latvia	0.43	Slovenia	0.47	Estonia	0.40	Austria	0.65
Spain	0.34	Estonia	0.43	United Kingdom	0.45	Austria	0.40	Ireland	0.59
Lithuania	0.31	Moldova	0.42	Spain	0.42	Latvia	0.38	Tunisia	0.59
Latvia	0.29	Spain	0.37	Estonia	0.32	Moldova	0.37	Czech Republic	0.58
Hungary	0.27	Belarus	0.34	Greece	0.31	Hungary	0.36	Bulgaria	0.58
Estonia	0.24	Ukraine	0.33	Latvia	0.26	Belarus	0.34	Portugal	0.56
Greece	0.24	Bulgaria	0.31	Poland	0.26	Ukraine	0.34	Moldova	0.56
Portugal	0.21	Egypt	0.30	Portugal	0.22	Bulgaria	0.32	Poland	0.48
Poland	0.20	Jordan	0.26	Czech Republic	0.21	Lithuania	0.27	Hungary	0.47
Bulgaria	0.19	Slovak Republic	0.26	Bulgaria	0.19	Slovak Republic	0.24	Slovak Republic	0.47
Czech Republic	0.19	Greece	0.23	Hungary	0.17	Greece	0.23	Ukraine	0.47
Slovak Republic	0.18	Czech Republic	0.20	Belarus	0.15	Poland	0.22	Morocco	0.45
Belarus	0.15	Lithuania	0.19	Egypt	0.14	Czech Republic	0.20	Cyprus	0.35
Ukraine	0.14	Poland	0.19	Slovak Republic	0.11	Jordan	0.16	Lithuania	0.33
Romania	0.11	Romania	0.15	Ukraine	0.10	Portugal	0.16	Romania	0.31
Egypt	0.10	Portugal	0.15	Tunisia	0.09	Romania	0.13	Latvia	0.26
Tunisia	0.10	Morocco	0.10	Romania	0.09	Morocco	0.12	Egypt	0.25
Morocco	0.05	Tunisia	0.09	Morocco	0.05	Tunisia	0.07		

[i] Spatial proximity is not the only kind of proximity that may be helpful in the process of knowledge exchange. Boschma (2005) identifies five dimensions of proximity: cognitive, organisational, social, institutional and geographical. Marrocu *et al*. (2012) recently provide an exploratory analysis which operationalises these concepts by applying them to European regions spillovers.

[ii] In a few cases, when necessary and feasible, missing data have been estimated.

[iii] When a patent has more than one inventor/applicant, a proportional share is attributed to each inventor. If inventors reside in different countries, the patent is attributed proportionally to each country.

[iv] For EPO patents the share of institutions in total applicants is usually estimated to be higher than 90%.

[v] Several measures have been suggested in the literature, starting with the patent citations used by Jaffe *et al*. (1993), and including commercial exchanges, human capital mobility and so on.

[vi] It should, however, be noted that patents by inventor's country of residence registered a general increase (with the exception of Israel) during the years under examination: there was a remarkable 82% increase from 2000 until 2008. This is particularly true for Armenia, Georgia and Lebanon (respectively, +240%, +210% and +175%).

[vii] Where data is available it is possible to assess the evolution of R&D expenditure in the latest decade. It is thus possible to note that the biggest effort in increasing R&D expenditure was made by Tunisia with an increment of 72% during the period starting from 2000 until 2005 (latest available year). Many other countries have not experienced big changes in their R&D investments: Ukraine, for example, has maintained its effort of about 1% of GDP constant for the whole period (2000-2007). Israel's R&D expenditure remained constant (above 4% of GDP) for several years but increased during the latest period. Finally, Algeria has followed a decreasing trend, reaching its lowest share of 0.07% of GDP in 2005.

[viii] This section focuses exclusively on the relationships between ENCs and the EU. We therefore neglect here the relationships between ENC and other parts of the world, or among ENCs themselves (this latter been rather weak). These issues are addressed in Autant-Bernard and Chalaye (2012).

[ix] This analysis, based on simple OLS regressions, allows us to identify the best output-input combination for each output indicator, but it cannot be used to make any inference, and therefore any comparison with previous KPF estimation, for two reasons. On the one hand, the sample is very limited and explanatory variables suffer from multicollinearity; on the other hand, the analysis is performed for total values for patents and publications, as in the subsequent DEA, rather than for per-capita values, as it is commonly done in the empirical literature on KPF.

[x] Input-oriented models are more suitable when the output is considered to be fixed and the key optimisation problem is related to the efficient use of inputs, the cost of which has to be minimised.

[xi] It is worth noting that the goodness of fit of the estimated models greatly increases when external networks are included while suggesting their relative importance for knowledge creation.

[xii] Previous empirical studies on DEA at country level (such as Guan and Chen 2012; Fu and Yang 2009; Cullmann *et al*. 2009) used more restricted sample and mainly for OECD countries.

[xiii] An updated analysis of the innovative performance of these two countries can be found in Aslamazishvili (2013) and UNESCO (2014) for Georgia and Armenia, respectively.