4.1 Introduction

Since the early literature on human capital, countless theoretical and empirical studies have aimed to identify knowledge as the main determinant of economic performance. Enhanced econometric techniques – accompanied by the availability of rich data sets on, for instance, innovation, education, patents or patent citations – have fostered a wealth of studies on the spatial characteristics which impact on the flow of knowledge across space (Faggian and McCann, 2006). These studies proved the existence of non-market knowledge externalities, defined as Knowledge Spillovers (KSs), which travel in space around the origin of new knowledge, but are subject to dire distance-decay processes. The identification of KS mainly took place by empirically verifying over what distance on average patent citations travel, or through the application of recent advances in spatial econometrics to regional knowledge production functions (henceforth, KPFs) or to regional growth regressions (Acs et al., 1994).

Recently, a new approach was proposed to capture potential KSs, through an application of a spatial filter applied to the dependent variable of a traditional KPF (Caragliu and Nijkamp, 2012; Caragliu and Del Bo, 2011). However, the notion of space underlying this work is purely geographical. While geographical space is often a good proxy for the implicit channels along which knowledge flows, it certainly fails to make such channels explicit, and therefore provides only limited insight into the topic of KS, other than the pure identification of their existence, and an indication of the relevance of distance-decay functions. Such a shortcoming has been partly motivated by the relative lack of data and computing power on alternative notions of space. Regional scientists and economists have rarely tried to overcome this gap, and have seldom attempted to encompass in one single study different notions of space.

In this chapter we aim to fill this gap, and propose a critical review of previous findings on the notions of proximity, which allow us to identify five main typologies of space (geographical, relational, social, technological, and cognitive), over which knowledge is expected to travel. These five types are then used to define five weight matrices, on the basis of which the above-mentioned econometric transformation is applied in order to study outward knowledge spillovers (henceforth, OKSs).

This chapter is organized as follows. In Section 2 we resume the long-standing debate on the dichotomy of knowledge as a public versus a private good, thus motivating our measure of KSs, and provide a critical review of the different notions of space and proximity employed in theoretical and applied work on KSs. We also provide an explanation of the possible underlying mechanisms that yield a rationale for the use of more complex notions of proximity in the field of KS. Section 3 then summarizes the methodology for the empirical estimation of our model. The data set collected for the present chapter and our measures of proximity are explained in Section 4. The estimation results are presented in Section 5. Finally, Section 6 makes some concluding remarks and brief comments on the policy implications of our findings.
4.2 Literature review

4.2.1 Proximity in regional research

From an economic standpoint, knowledge can in most cases be defined as a partially public (i.e. non-rival and non-excludable) good. Its partially non-rivalrous nature has also been pinpointed in classical writings. In 1813, for instance, Thomas Jefferson writes in a letter to Isaac Mc Pherson “If nature has made any one thing less susceptible than all others of exclusive property, it is the action of the thinking power called an idea....Its peculiar character...is that no one possesses the less, because every other possesses the whole of it” (Washington, 1853, p. 180; see also Suber, 2009). The imperfect excludability of knowledge is, on the contrary, modelled in Lucas (1988), where agents invest in their own education without fully internalizing the benefits stemming from such investment which also accrue to the rest of the society. It therefore seems plausible to assume that at least part of the codified and tacit knowledge produced in a region transmits to other areas because of imperfect rivalry and imperfect excludability.

In the process of spatial diffusion, knowledge faces distance-decay effects. Conceptual and empirical research in regional science has addressed and clarified the implications of spatial barriers with varying degrees of success (Krugman, 1998). However, recent advances in spatial economics have provided a rich set of theories explaining the role of complex forms of proximity in economic interactions. In the field of knowledge production and diffusion, there is a general consensus that not all the positive fallout of knowledge production is locally retained (Jaffe et al., 1993; van Geenhuizen and Nijkamp, 2012); in fact, some scholars (e.g. Shearmur and Bonnet, 2011) even argue that the local production of knowledge is uncorrelated with local economic performance. Such critiques call for a profound analysis of the economic mechanisms that drive the ways in which KSs travel across space.

Various attempts have been made since the mid-1950s to systematize the literature on different forms of proximities. Traditionally, economic models have tended to ignore the effects of distance among actors as a major determinant of the outcome of economic interactions. While this relative lack of attention stimulated Walter Isard’s (e.g. Isard, 1956) early contributions and the very birth of regional science, only relatively recently has economics begun to include space explicitly into formal models (for an overview, see, e.g., van den Bergh et al., 1998). In the last decade of the twentieth century, regional scientists stressed more aspects of the relevance of space in economic interactions, and prompted the analysis of alternative forms of proximities beyond just geographical space. This was true in particular for the ‘learning region’ approach (with the concept of institutional proximity: see Lundvall and Johnson, 1994) and the ‘milieu innovateur’ and the ‘industrial district’ theories (which focused more on relational proximity: see Aydalot, 1986; Camagni, 1991; Becattini,
However, such literature has often, and mostly because of previous limitations of computing power in econometric software, been unable to account for more complex definitions of proximity, as opposed to a definition based simply on geographical space. The contributions by the New Economic Geography (Fujita et al., 1999) are noteworthy here.

Around the mid-1990s, there was a resurgence of applied studies, stimulated by pioneering work on the economic rationale for alternative approaches to proximity (Crevoisier, 1996; Boschma, 2005; Torre and Gilly, 1999; Capello, 2009), and made possible by the increase in the computing power of standard econometric software. While the objectives of these studies were sometimes diverse (mostly concerning the determinants of KSs and regional growth), all share an increased interest in the indirect channels through which proximity affects economic interactions. In fact, physical distance in standard KS studies can be considered as a ‘black box’. As pointed out in Grosjean (2011), “distance matters in itself, but is also a proxy for other determinants of familiarity”.

In this strand of literature, various forms of proximity have been identified as the channels through which knowledge can be transmitted. Figure 20 shows most definitions of proximity as they have been variously framed over the past two decades, in the literature summarized above.

A first school of thought identifies in relational proximity a cause for the emergence of local increasing returns to regional development. According to the milieu innovateur school, developed by the GREMI group,37 regional stocks of knowledge will accumulate through cooperative learning processes, enabled and fostered by spatial proximity (which enters the theoretical foundations of the milieu literature as a form of ‘atmosphere’ effects), network relations (where long-distance relationships can be as effective as face-to-face contacts in a selected set of knowledge-intensive relationships), socio-cultural interaction, and creativity. According to this view, the thickness of relationships among local actors enhances the likelihood of innovative types of behaviour, which in turn foster economic performance. More recently, network components associated with the notion of relational proximity have also been analysed in interesting empirical studies on the role of relational proximity as means of fostering KSs (see, e.g., Maggioni and Uberti, 2009).

Simultaneously, the learning region theory38 stresses the role of institutional distance in economic interactions, via an insightful analysis of the interactions between local actors belonging to a system of homogeneous socio-economic and institutional environments.

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37 The GREMI (Groupe de Recherche Européen sur les Milieux Innovateurs) was created by Philippe Aydalot in 1984, and focused its research on the determinants of the spatial concentration of small firms.
38 See Lundvall and Johnson (1994); Morgan (1997).
Figure 20. A classification of proximities

Note: The empty brackets in the bottom circle suggests other possible definitions of proximity in the KS literature
Conceptually similar to the notion of institutional proximity is the idea that organizational proximity may also make economic transactions easier. However, in this case much confusion arises when different schools use this label to address (at least partially) different concepts. In particular, the French school of proximity dynamics (Bellet et al., 1993) stressed the relevance of relationships in the effects of low levels of organizational dissimilarities among actors within pre-determined social structures. This implies a partial overlapping with the milieu innovateur approach to proximity.

Analogously, some confusion has arisen concerning the notions of cognitive and technological proximity. The latter has mainly been the focus of industrial organization studies (Orlando, 2004; Jaffe and Trajtenberg, 1999), where, along with the impedance offered by geographical space, knowledge is found to travel more easily across narrowly-defined, and compatible, technological classes. However, a recent and successful wave of studies based on the notion of “related variety” (Broekel and Boschma, 2012) finds that cognitive proximity may, to a certain extent, increase the likelihood of cross-fertilization among actors. This cross-fertilization requires that people speak the same scientific language (i.e. they belong to the same technological paradigm), while at the same time they are separated in terms of narrower technological classes. This in turn generates a mechanism of creative resonance based on the pool of ideas from relatively different technologies available within the same technological class (hence the term “related variety”) which ultimately leads to innovation. Our definition of cognitive proximity follows these ideas, extending this concept from within-region to cross-regional technological cross-fertilization.40

All these definitions of proximity do not imply that the distance-decay effect of economic interactions is dead. In fact, most empirical work usually finds that these forms of proximity complement the role of geographical distance as a factor which impedes the flow of knowledge. This mutual complementarity is based on the notion of knowledge tacit-ness. According to Polanyi’s work (Polanyi, 1967), standard, codifiable knowledge can be disentangled from what cannot be easily conveyed in written form, and thus formalized. This relates to the dichotomy know-what versus know-how, the latter residing in people’s minds and not being transferrable without some loss of relevant information (Johnson et al., 2002). If knowledge is really at least partially tacit, then it travels more easily across shorter

39 Usually, related variety characterizes actors co-localized within the same region. In this chapter we use a measure of inter-regional related variety, first developed in Capello and Caragliu (2012), which extends this notion to cross-regional knowledge transfer.
40 Because cross-fertilization from technologically-proximate classes definitely alters the perception of the world of agents who are exposed to such knowledge, we posit that cognitive proximity between pairs of regions may also be compatible with a narrower definition. “Cognitive proximity, broadly understood, denominates similarity in the way people perceive, interpret, understand and evaluate the world” (Hüber, 2011). In fact, the notion of cognition implies “the mental process of knowing, including aspects such as awareness, perception, reasoning, and judgment” (The American Heritage Dictionary of the English Language, 2000).
distances, since it requires other forms of contact between individuals to be understood, and efficiently decoded and deployed (Howells, 2002).

It should finally be noted that the concept of social and cultural proximity can be linked to the concept of social capital. In the 1980s and 1990s, some influential studies (Coleman, 1988; Putnam et al., 1993; Putnam, 2000; Fukuyama, 1995) attracted the attention of academicians, practitioners and policy makers on the interesting issue of how norms, networks, and institutions (in a single expression, social values) determine the way societies interact. Social incentives are at the heart of this literature. Do more intense interactions between people generate a greater sense of community? Does a higher level of trust among citizens reduce the transaction costs associated with each interaction, and if so, through which channels? According to most studies on social capital, the answer to such questions is “yes”. Because social capital is inherently space-specific, and cannot be transplanted without incurring disproportionate costs, inter-regional differences in social capital may hamper the flow of knowledge across space (Agrawal et al., 2006).

So far, this rich (and growing) literature has seldom brought together these somewhat orthogonal areas of research. In the present study, we integrate all these relevant views on proximity and adopt an econometric transformation designed by the authors to measure potential KSs according to each of these forms of proximity.

4.2.2 Preconditions and channels of knowledge transfer

The extant literature on knowledge transfer can be classified as encompassing two major strands. On the one hand, several empirical studies have focused on the physical vehicles that channel knowledge transfer in space. This is a relevant field of research, since the object of analysis is the carrier of knowledge (usually, people or freight). Although this chapter does not directly deal with these topics, it is here worth mentioning some of the most frequently analyzed vehicles of knowledge transfer, including migrations (Oettl and Agrawal, 2008; Faggian and McCann, 2009), international trade and Foreign Direct Investments (De La Potterie and Lichtenberg, 2001), Multinational Companies (Gupta and Govindarajan, 2000), patent citations (Jaffe et al., 1993), and scientific cooperation (Capello and Caragliu, 2012).

A second strand of literature, that represents the approach followed in this chapter, focuses instead on the preconditions for all such channels to enhance knowledge transfer in space: this process requires in particular some type of proximity between actors and regions. In this

41 A recent exception is Guiso et al. (2009), where nevertheless the focus of analysis is on the determinants of bilateral trust among pairs of countries. In the regional science field, the inclusion of multiple concepts of non-geographical proximity in the empirical analysis of knowledge creation and diffusion processes includes, among others, Maggioni et al. (2007) and Marrocu et al. (2011).
second case, some physical channel of knowledge diffusion is assumed to be implicitly valid, while the focus of the empirical analysis is on the preconditions needed for such channels to effectively transfer knowledge, in the form of various types of proximity.

Although empirical analyses on the preconditions for knowledge transfer discussed in Section 2.1 have seldom been carried out, the literature offers some examples of empirical studies which explore the mechanisms underlying each form of proximity in the process of knowledge diffusion. In other words, how does knowledge physically spread? Are those who advocate the “death of distance” (e.g. Cairncross, 1997) right? This second strand of literature is briefly summarized in Table 20, showing some possible preconditions on the basis of which knowledge may potentially travel.

<table>
<thead>
<tr>
<th>Type of proximity</th>
<th>Channels through which knowledge spreads</th>
<th>Type of indicator</th>
<th>Mechanisms facilitating knowledge diffusion</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographical</td>
<td>Face-to-face contacts</td>
<td>Differences in regional stocks</td>
<td>Higher probability of meeting</td>
</tr>
<tr>
<td>Social/cultural</td>
<td>Parallel decisions, taken because cultural values are similar</td>
<td>Differences in regional stocks</td>
<td>Lower communication costs</td>
</tr>
<tr>
<td>Technological</td>
<td>Technological spillovers</td>
<td>Differences in regional stocks</td>
<td>Higher probability of cross-fertilization, mostly through reverse-engineering</td>
</tr>
<tr>
<td>Cognitive</td>
<td>Non-verbal communication, tacit knowledge</td>
<td>Differences in regional stocks</td>
<td>Sharing of a common communication code</td>
</tr>
<tr>
<td>Relational</td>
<td>Informal networks</td>
<td>Flows between pairs of regions</td>
<td>Lower transaction costs</td>
</tr>
</tbody>
</table>

Source: Authors’ elaboration

**Geographical proximity**, which lies behind most current studies of knowledge transfer, is at best a proxy for the real underlying channels of knowledge transfer. It is implicitly based on the assumption that knowledge spreads only via face-to-face contacts, implying that the closer the agents are, the higher the probability of meeting.

This concept hides some other potential determinants of knowledge flows across space. For instance, **social proximity** among agents may imply lower communication costs (McCloskey and Klamer, 1995), and simultaneously increase the likelihood that decisions are made by people with a similar mindset.

Agents of regions with a similar technological specialization (i.e. those enjoying **technological proximity**) may, in turn, find it easier to access potential technological spillovers, by means of reverse engineering technologically-compatible products (Padilla-
Pérez, 2008). Technological proximity may therefore foster knowledge diffusion by increasing the probability of the cross-fertilization of ideas.

**Cognitive proximity** is instead based on a relatively new concept, viz. that of cognitive capital. There have been two convincing definitions of this new concept. On the one hand, Boschma and co-authors extend the notion of related variety to cognitive proximity, i.e. they posit that industries and regions must be cognitively neither too close, nor too distant, in order to trigger mutual learning processes: “Some degree of cognitive proximity between two sectors ensures effective communication and common understanding, and some degree of cognitive distance is needed to avoid cognitive lock-in” (Boschma et al., 2012: p. 243). On the other hand, cognitive capital has also been recently defined as “(...) mental processes and resulting ideas, reinforced by culture and ideology, specifically norms, values, attitudes, and beliefs that contribute cooperative behavior and mutually beneficial collective action” (Uphoff, 1999, p. 218). This definition breaks down the concept of social capital into two main axes, viz. structural and cognitive social capital. Proximate regions in terms of their (mostly scientific and industrial) culture and ideology (i.e. in their cognitive social capital) are expected to share a common communication code, thereby fostering knowledge transfer. In our view, this definition, based on the notion of cognition, is fully compatible with that of Boschma and co-authors.

**Relational proximity** is defined as the capability of regions to learn through cooperation. This concept has been thoroughly examined by the GREMI school, although its validity has seldom been empirically verified. Agents (and, in the present case, regions) being relationally proximate take part in processes of collective learning (Camagni, 1991; Perrin, 1995). In this chapter, relational proximity is measured with the intensity of scientific relations between pairs of regions (i.e. by the set of short- and long-distance networks that enable the easier flow of knowledge across space).

In this chapter, one major aspect of novelty concerns the way the usual approach to KS is carried out. In fact, instead of verifying the channels (vehicles) through which regions can benefit from knowledge generated outside, we verify on the basis of which non-geographical preconditions regions can attract KSs.

This chapter argues that none of these forms of proximity alone is sufficient to fully account for all channels of knowledge diffusion. However, each of these proximities is based upon a convincing theoretical explanation of the mechanisms and channels of knowledge diffusion that they represent. Therefore, in Sections 3-5 we test empirically the validity of each of these forms of proximity as potential preconditions for knowledge diffusion.

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42 This concept has been operationalized within a regional growth model in Caragliu and Nijkamp (2014).
4.3 Methodology, research question and estimation model

The first research task was to define different types of proximity. Next, it was necessary to identify a measure for each type of proximity and to employ it within the conceptual framework above described. A new measure of KSs will be defined here and employed in order to analyse its determinants in a regional setting. In this subsection, we briefly introduce this econometric transformation, initially based on geographic space, and move a step forward by asking the following research question:

**RQ. Which non-geographic preconditions transmit KSs?**

In other words, we employ the econometric framework presented below in order to test the change in the estimated parameters induced by applying the transformation with the use of different proximity matrices other than the simple one based on just geographic space.

Suppose the regional stock of knowledge is produced according to a linear KPF as:

\[
Y = X\beta + \varepsilon, \quad (4.1)
\]

where matrix \(X\) encompasses all relevant determinants of regional knowledge production, and \(Y\) represents a measure of knowledge. Here, knowledge is measured by Total Factor Productivity (henceforth, TFP).\(^{43}\)

Regional TFP is typically affected by spatial autocorrelation, i.e. its values are distance-sensitive and tend to be clustered in space. In this case, spatial econometrics clarifies how linear techniques would yield biased parameter estimates. In fact, eq. (4.1) can be rewritten to take into account spatial autocorrelation patterns as follows:

\[
Y = \rho W Y + X\beta + \varepsilon, \quad (4.2)
\]

where \(W\) is a (spatial) weight matrix, and \(\rho\) is the spatial autocorrelation coefficient. The latter displays a behaviour similar to that of the equivalent parameter in time series modes.

In Eq. (4.2), terms must be rearranged by bringing the \(\rho W Y\) term to the left-hand side, isolating \(Y\) and pre-multiplying the matrix \((I-\rho W)^{-1}\) to the \(X\) matrix and the \(\varepsilon\) vector. The \((I-\rho W)\) matrix is obtained as follows:

\[
B = (I - \rho W) = \begin{pmatrix}
1 & 0 & \ldots & 0 \\
0 & 1 & \ldots & 0 \\
0 & \ldots & \ldots & 0 \\
0 & 0 & \ldots & 1
\end{pmatrix} - \rho \begin{pmatrix}
w_{11} & w_{12} & \ldots & w_{1n} \\
w_{21} & w_{22} & \ldots & w_{2n} \\
\vdots & \vdots & \ldots & \vdots \\
w_{n1} & \ldots & \ldots & w_{nn}
\end{pmatrix}, \quad (4.3)
\]

\(^{43}\) This means that we calculate the residuals of a production function of the form \(Y = AK^\alpha L^{1-\alpha}\). The stock of capital is calculated with the perpetual inventory method, assuming a yearly constant depreciation rate of 2.5 per cent, on the basis of EUROSTAT’s Gross Fixed Capital Formation series, with 1990 as the base year.
where \( B \) is the Greek upper-case letter \( \beta \), from the word meaning “weight”; \( \hat{\rho} \) is the (estimated) autocorrelation parameter; and \( w_{ij} \) represents distance values between analysed regions. Eq. (4.3) shows that the result of this calculation is an \((n \times n)\) matrix. This matrix, after being inverted, transforms each variable in the \( X \) matrix into its contribution, to and from each region, to the dependent variable. In other words, it can be interpreted as an input-output matrix, where each element shows the weight to be assigned to each observation in the vectors stacked in the \( X \) matrix in order to obtain inward and outward flows of these elements to the region observed.

Finally, by pre-multiplying matrix \( B \) by the TFP vector we obtain our measure of KSs. Such a measure represents the balance of positive and negative absolute knowledge flows across regions: when it takes on a positive value, it implies the region potentially attracts more knowledge than what it transmits outside. When this measure is negative, instead, the net knowledge balance is negative, i.e. the region produces more knowledge than what it can retain internally.

The first step to apply our transformation entails, therefore, the estimation of the KPF. In this chapter we follow recent applied studies on the main determinants of productivity; in particular, the variables included in the instrumental estimates of the KPF are chosen according to the sample employed in Loko and Diouf (2009) and Eichler et al. (2005). Our KPF takes therefore the form:

\[
TFP_{r,t} = \alpha + \beta^*HC_{r,t} + \gamma^*ACCESS_{r,t} + \delta^*FDI_{r,t} + \zeta INST_{r,t} + \epsilon_{r,t},
\]

where indices \( r, i \) and \( t \) indicate the region, country and time, respectively. Regional TFP may clearly depend not only on a set of regional determinants, which include the level of human capital, the level of accessibility, the intensity of FDIs, and the quality of regional institutions. Other, country-varying, factors may affect regional productivity: these may include, among others, the level of taxes; political institutions; the quality and type of the schooling system; the inflation rate;\(^{44}\) government size; and national industrial regulation. Such controls are included with the use of country fixed effects. The results of estimating the a-spatial KPF are instead shown in the next Section.

Once our transformation has been employed, we obtain \( n \) measures of potential KSs, one for each weight matrix adopted; the KS measure takes on positive or negative values if, respectively, inward or outward potential knowledge flows prevail in the region.\(^{45}\)

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\(^{44}\) Regionally-varying price levels are not available.

\(^{45}\) Interestingly, the measure of knowledge spillovers here calculated is based on focusing on inward knowledge spillovers. This is reflected in the choice of row-standardized proximity matrices. Were the opposite assumed, the use of column standardized matrices would be recommended instead (Ponds et al., 2010).
Finally, and following our previous work on this topic, we propose the following implicit form equation for KSs:

\[ \text{Knowledge spillovers}_i = f (\text{Absorptive Capacity}_i, \text{R&D}_i, \text{R&D}_j), \quad (4.5) \]

where region \( i \) is the region under consideration; and regions \( j \), with \( j \neq i \), are all other regions. A major departure from previous work lies in a more careful definition of absorptive capacity, which is measured here, following Cohen and Levinthal (1990), as the cumulated stock of patents granted by the European Patent Office between 1999 and 2008.\(^{46}\)

In our conceptual framework, absorptive capacity takes on a double nature. On the one hand, local R&D expenditure fosters the attraction of KSs: this implies we expect a positive sign for the intensity of R&D and the level of absorptive capacity within each region, as local innovative activities increases the likelihood of attracting new knowledge (i.e. a process of inter-regional knowledge diffusion). By the same token, long-run investment in R&D, leading to the accumulation of technical knowledge embedded in the stock of patents, increases the local capability to understand, decode, and fully exploit newly produced knowledge. As such, we may expect eq. (4.5) to meet the following plausible expectations:

- **A positive sign for the local absorptive capacity term.** Even assuming the external world has no absorptive capacity at all (i.e. the ‘pull’ effect equals zero), a higher stock of previously accumulated knowledge within the region fosters its chances to retain internally the positive fallout of R&D activity.

- **A positive sign for local R&D intensity.** More expenditure in innovation activities in a region provides the rationale for the attraction of KSs;

- **A negative sign for surrounding areas’ absorptive capacity.** In a way, this last expectation is the reverse of the second point: when neighbouring regions invest in R&D, they tend to exert a pull effect on locally produced knowledge. Their socio-economic soil is more fertile and ready to reap the positive effects of externally produced knowledge, through commuting patterns, input output mechanisms, and formal and informal exchange of new ideas. Finally, this last sign is expected to be negative for one more reason. KSs happen through several different channels, one of which is trade: through reverse engineering, firms can acquire technology embedded in traded goods (Padilla-Pérez 2008). More knowledge accumulated in external regions implies therefore a pull effect for the locally-produced knowledge.

\(^{46}\)The stock of cumulated knowledge, viz. the measure of regional absorptive capacity, is calculated with a perpetual inventory method. The first year’s stock is calculated as the total number of patents granted in 1990 discounted by 0.025 (an average yearly discount rate \( \delta \) of 2.5 per cent) plus the labour productivity growth rate. Subsequent years are then built, defining \( K(t) \) which is the stock of knowledge at time \( t \), as \( K(t) = K(t-1)*(1-\delta) + \Delta (K(t)). \) The resulting time span covers the period 1999-2008.
The negative sign for surrounding areas’ absorptive capacity can be finally interpreted as a ‘pull’ effect: the existence of other regions with a high absorptive capacity exerts a competitive pressure on the positive leakages from local knowledge production. Firms outside each region continuously look for new sources of potentially revenue- and productivity-enhancing knowledge; as such, the higher the external world’s absorptive capacity, the higher the likelihood that KSs will take place.

4.4 The data set

In order to test eq. (4.5), we collected a new database covering the decade 1999-2008, with EUROSTAT data on gross expenditure in R&D, regional labour force, value added (in constant 2000 prices), and capital stock.47 Besides, data have been collected for the variables used in the first-stage estimate of the KPF discussed in Section 3. Sources of these data are shown in Section 1 of the Technical Appendix.

The main aim of this chapter is instead to encompass in one single study a comprehensive classification of the various types of proximities in the analysis of KSs. We define five types of proximity, and use each proximity matrix to construct the measure of KS described in the previous section. A first attempt to capture the role of different types of proximity in the generation of KSs among European regions is carried out in Basile et al. (2012). A more recent contribution (Capello and Caragliu, 2012) moves a step forward in this direction by building indicators for different forms of non-geographical proximity; these indicators are then used to verify the impact of various proximities on the intensity of scientific cooperation.48 We follow this last approach, and identify the following indicators of proximity between pairs of regions (Table 21).

For geographical proximity, for each pair of regions we calculate the traditional distance in arcminutes between pairs of centroids.

For relational proximity, following Maggioni and Uberti (2009) and Basile et al. (2012), we calculate co-participation between pairs of regions in the joint FP5 projects.49 This is also in

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47 The stock of physical capital is calculated with the perpetual inventory method, on the basis of EUROSTAT’s gross fixed capital formation time series. The base year for all calculations is 1995, while we assume an yearly depreciation rate of 2.5 per cent.

48 In turn, the present work has been conceived within the framework of the ESPON KIT project (http://www.espon.eu/main/Menu_Projects/Menu_AppliedResearch/kit.html).

49 European FPs are aimed at fostering scientific research in the European Union. The 5th wave of FPs covered the period 1998-2002. We chose FP5 in order to cover the highest number of regions. The FP5 data set has been collected in European Commission (2005). A more recent wave, the 6th, is also available, but with no geo-referentiation, which is necessary to calculate inter-regional relational proximity.
line with a rich literature dealing with R&D collaboration (e.g. Scherngell and Barber, 2009, 2011; Autant-Bernard et al., 2007).\textsuperscript{50}

Table 21. Measuring different types of proximity

<table>
<thead>
<tr>
<th>Concept of proximity</th>
<th>Indicator</th>
</tr>
</thead>
<tbody>
<tr>
<td>Geographic proximity</td>
<td>Geographic distance between pairs of centroids</td>
</tr>
<tr>
<td>Relational proximity</td>
<td>$rel_{ij} = copartFP_{ij}$</td>
</tr>
<tr>
<td>Social proximity</td>
<td>$soc_{ij} = \sqrt{\sum_{q=1}^{Q} \left( x_{qij} - x_{qij} \right)^2 / \sum_{q=1}^{Q} \left( x_{qij} + x_{qij} \right)}$</td>
</tr>
<tr>
<td>Cognitive proximity</td>
<td>$cog_{ij} = \sum_{s2}^{7} \left[ (x_{s2ij} \times x_{s2 j}) \left( \sum_{s3}^{m} (x_{s3ij} - x_{s3 j}) \right) \right]$</td>
</tr>
<tr>
<td>Technological proximity</td>
<td>$tech_{ij} = \sum_{q=1}^{Q}</td>
</tr>
</tbody>
</table>

Source: Author’s elaboration

For \textit{technological proximity}, we calculate the absolute distance between regions in terms of regional specialization (measured with location quotients in NACE 2-digit manufacturing sectors).

For \textit{social proximity}, we calculate the Euclidean average distance between regions in terms of social capital. The wealth of regional social capital is measured using a principal component analysis (PCA) on four social capital axes, as traditionally defined in previous studies on this topic (see, for instance, Putnam, 2000).\textsuperscript{51} In this case, the indicator of proximity is discounted by the sum of each region pair’s social capital, under the assumption that differences in social capital matter more for region pairs including at least a region with low levels of social capital.

Finally, the last proximity measure calculated deserves specific attention. Following Capello and Caragliu (2012), \textit{cognitive proximity} is captured, by analogy with the literature on related variety, as the variety of patenting activity within 3-digit classes, multiplied by the similarity within 2-digit classes, between region pairs. Nevertheless, unlike previous work by Broekel and Boschma (2012), the notion of related variety is extended to the cross-regional case. In particular, we posit that regions can reap maximum benefits from other knowledge-

\textsuperscript{50} The use of FP5 co-participation data represents a biased measure of learning through cooperation, since typically the spatial distribution of universities is uneven across space. Regions lacking prestigious or internationally-active universities may in fact be characterized by the presence of other institutions capable of cooperating internationally.

\textsuperscript{51} The details on such calculations are given in Section 2 of the Technical Appendix.
generating regions when they are neither too far, nor too close (from an industrial perspective).\textsuperscript{52}

Overall, our data set covers a set of 264 European NUTS2 regions, for the period 1999-2008. This yields a total of 2640 observations.\textsuperscript{53}

The proximity measures built here do indeed capture different ways in which economic interactions are structured over space. Table 22 shows the Pearson’s correlation indices calculated between all pairs of proximity measures. Values range from -0.18 to 0.14; indeed, proximity measures show a relatively low degree of mutual correlation, which supports the idea behind the present chapter.

**Table 22. Correlation matrix among proximity matrices**\textsuperscript{54}

<table>
<thead>
<tr>
<th></th>
<th>Relational</th>
<th>Cognitive</th>
<th>Technological</th>
<th>Social</th>
<th>Geographical</th>
</tr>
</thead>
<tbody>
<tr>
<td>Relational</td>
<td>1.00</td>
<td>-0.08</td>
<td>-0.09</td>
<td>-0.05</td>
<td>0.07</td>
</tr>
<tr>
<td>Cognitive</td>
<td>-0.08</td>
<td>1.00</td>
<td>0.12</td>
<td>0.11</td>
<td>-0.02</td>
</tr>
<tr>
<td>Technological</td>
<td>-0.09</td>
<td>0.12</td>
<td>1.00</td>
<td>0.14</td>
<td>-0.08</td>
</tr>
<tr>
<td>Social</td>
<td>-0.05</td>
<td>0.11</td>
<td>0.14</td>
<td>1.00</td>
<td>-0.18</td>
</tr>
<tr>
<td>Geographical</td>
<td>0.07</td>
<td>-0.02</td>
<td>-0.08</td>
<td>-0.18</td>
<td>1.00</td>
</tr>
</tbody>
</table>

*Source: Authors’ calculations*

**4.5 Estimation results**

This section aims at highlighting the relevance of different channels of knowledge diffusion across European regions. Eq. (4.5) can be rewritten in linear form as:

\[
KS_{r,t} = \alpha + \beta AC_{r,t} + \gamma R & D_{r,t} + \delta R & D_{j,t} + \epsilon_{r,t}
\]  

(4.6)

where \(r, j, \) and \(t\) indicate region \(r,\) region \(j, j\neq r,\) and time \(t,\) respectively.

---

\textsuperscript{52} More details of the calculations needed to obtain the cognitive proximity matrix are available in Section 4 of the Technical Appendix of the chapter.

\textsuperscript{53} Further details on the various proximity matrices are given in Section 1 of the Technical Appendix.

\textsuperscript{54} Table 22 differentiates with respect to Table 11, which is otherwise conceptually similar, along several different dimensions. The most important difference is the use made in Table 22 of a matrix of geographic proximity, instead of the matrix of geographic distance as is done in Table 11. Besides, some proximity matrices employed in this chapter present minor differences with respect to the ones discussed in Chapter 3.
Our previous work on a similar equation suggested that absorptive capacity and R&D intensity in the originating region are expected to attract KSs to the host region, which are actually negatively correlated with R&D intensity in neighbouring regions. In this section, we first briefly present the results of estimating the a-spatial KPF, which is instrumental to calculating our measures of KSs (Section 4.5.1); and, next, we present the main findings of estimating model (4.6), with the use of the proximity matrices defined in Section 4.4. Across all estimates of both first (KPF) and second (KS) stage, all variables on the RHS of the equations are time-lagged, in order to minimize endogeneity issues.

4.5.1 The knowledge production function

The results of estimating eq. (4.4) are shown in Table 23. All parameter estimates yield positive and significant estimates, with an interesting relative magnitude of the parameter estimated for regional institutions (Charron et al., 2014), which turns out to be more strongly related to regional TFP w.r.t. to both Human Capital and Accessibility. As for Human Capital, its estimated parameter loses significance as FDIs and regional institutions included in the estimates. The high significance of most Country fixed effects, finally, also testifies for the relevance of country-specific factors in determining regional productivity.

A second crucial step in calculating our measure is the assessment of spatial trends in the KPF. In this chapter, we move a step beyond our previous research, and identify spatial trends using Moran’s I statistics calculated on the basis of the five typologies of proximity described in Section 4.2. The results of this process are shown in Table 24, along with the estimated parameter of the spatially-augmented KPF.

The values of the $\rho$s shown in Table 24 are employed to calculate the dependent variables of the main estimates.

55 These estimates can be compared with those based on Spatial Auto Regressive (SAR) models, which are suggested on the basis of the inspection of the usual battery of tests discriminating between SAR and Spatial Error Models (SEM).

In this case, the Wald test of $\rho=0$ is rejected at the 95% confidence level, with a $\chi^2(1) = 4.806 (0.028)$, and the corresponding likelihood ratio test of $\rho=0$ is also rejected at the 95% confidence level, with a $\chi^2(1) = 5.240 (0.022)$. The SEM model presents the opposite results. The Wald test of $\lambda=0$ is not rejected at any confidence level, with a $\chi^2(1) = 0.004 (0.949)$, and the corresponding likelihood ratio test of $\lambda =0$ is also never rejected at any confidence level, with a $\chi^2(1) = 0.004 (0.949)$. Hence, it is clear that the SAR model should be preferred.
Table 23. Estimation results for the Knowledge Production Function (eq. 4.4)

<table>
<thead>
<tr>
<th>Dep. variable: regional Total Factor Productivity 1999-2008</th>
<th>Model</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant term</td>
<td></td>
<td>-0.08***</td>
<td>-0.05</td>
<td>-0.05*</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Human capital (% labour force with ISCED 5 and 6 education)</td>
<td></td>
<td>0.06**</td>
<td>0.07***</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
<td>(0.01)</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>0.06**</td>
<td>0.04*</td>
<td>0.04*</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Accessibility</td>
<td></td>
<td>-0.06**</td>
<td>0.07***</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Inward Foreign Direct Investments</td>
<td></td>
<td>-0.18***</td>
<td>0.17***</td>
<td>0.12***</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Quality of regional institutions</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.12***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.01)</td>
</tr>
<tr>
<td>Country Fixed Effects</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robust standard errors</td>
<td></td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td></td>
<td>0.49</td>
<td>0.49</td>
<td>0.51</td>
<td>0.52</td>
</tr>
<tr>
<td>Joint F test</td>
<td></td>
<td>297.47**</td>
<td>289.57**</td>
<td>283.83**</td>
<td>283.45**</td>
</tr>
<tr>
<td>Number of observations</td>
<td></td>
<td>2376</td>
<td>2376</td>
<td>2376</td>
<td>2376</td>
</tr>
</tbody>
</table>

Notes: Standardized coefficients reported. * = significant at the 90% level; ** = significant at the 95% level; *** = significant at the 99% level. Robust standard errors shown in brackets.

Table 24. Moran’s I statistics and values of the estimated ρ’s, according to different notions of proximity

<table>
<thead>
<tr>
<th>Type of proximity</th>
<th>Global Moran's I of regional TFP</th>
<th>Spatial autocorrelation coefficient of the KPF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Physical</td>
<td>0.07***</td>
<td>0.06***</td>
</tr>
<tr>
<td>Relational</td>
<td>0.16***</td>
<td>-0.01***</td>
</tr>
<tr>
<td>Social</td>
<td>-0.02***</td>
<td>-0.001***</td>
</tr>
<tr>
<td>Cognitive</td>
<td>-0.01</td>
<td>-0.01***</td>
</tr>
<tr>
<td>Technological</td>
<td>-0.02***</td>
<td>0.01***</td>
</tr>
</tbody>
</table>

Note: both coefficients are calculated as period averages (1999-2008) of the parameters estimated in the ten cross sections of data available

4.5.2 Main estimations

Section 4.5.2 presents the results of estimating the main model (eq. 4.6), with OLS estimates running from column 1 to column 5 (Table 25).
Table 25. Estimation results for the main model (eq. 4.6)

<table>
<thead>
<tr>
<th>Model</th>
<th>(1) Geographical</th>
<th>(2) Relational</th>
<th>(3) Social</th>
<th>(4) Cognitive</th>
<th>(5) Technological</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proximity matrix used</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant term</td>
<td>-0.008***</td>
<td>-0.01***</td>
<td>-0.02</td>
<td>-0.04*</td>
<td>-0.09***</td>
</tr>
<tr>
<td></td>
<td>(0.004)</td>
<td>(0.00)</td>
<td>(0.02)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Absorptive capacity</td>
<td>0.07***</td>
<td>0.04**</td>
<td>-0.02</td>
<td>0.04**</td>
<td>0.04**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.01)</td>
<td>(0.02)</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Local R&amp;D intensity</td>
<td>0.08***</td>
<td>0.04***</td>
<td>0.03</td>
<td>0.04***</td>
<td>0.04**</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.00)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Lagged R&amp;D intensity</td>
<td>-0.07**</td>
<td>0.04***</td>
<td>0.03</td>
<td>-0.05***</td>
<td>0.03**</td>
</tr>
<tr>
<td></td>
<td>(0.00)</td>
<td>(0.01)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Country fixed effects</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Robust standard errors</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>R²</td>
<td>0.12</td>
<td>0.09</td>
<td>0.02</td>
<td>0.49</td>
<td>0.48</td>
</tr>
<tr>
<td>Joint F test</td>
<td>11.19***</td>
<td>8.23***</td>
<td>1.79***</td>
<td>77.44***</td>
<td>77.93***</td>
</tr>
<tr>
<td>Number of obs.</td>
<td>2376</td>
<td>2376</td>
<td>2376</td>
<td>2376</td>
<td>2376</td>
</tr>
</tbody>
</table>

Notes: Standardized coefficients reported. * = significant at the 90% level; ** = significant at the 95% level; *** = significant at the 99% level. Robust standard errors shown in brackets.
Models 1-5 present OLS estimates of the main model, which vary because of the rotation of different definitions of proximity that enter the calculation of both the dependent variable and the lagged R&D intensity. Although these estimates use the same econometric transformation first proposed in Caragliu and Nijkamp (2012), the equation estimated and the data set used present minor differences; this being the case, this column cannot be compared with the main estimates in the original contribution.

For all specifications, the main findings on the role of local R&D as a net enhancer of KSs are confirmed, although the significance associated with this parameter is not significant at any conventional level for the estimates based on the social proximity matrix (Column 3).

The containment effect (i.e. the parameter associated to local absorptive capacity) presents unequivocal findings. Across all specifications, and, therefore, irrespective of the type of non-geographic precondition adopted, this empirical test yields a powerful confirmation that more KSs are attracted in the presence of a higher local absorptive capacity, even when other regions invest in R&D activity.

An interesting result emerges in terms of the lagged R&D investment parameter estimate. This last vector measures the potential competition stemming from all regions other than the analysed one, whereas the precondition for such spatial competition to take place is based on the various forms of proximity described above. While a competition effect does emerge on the basis of the geographical and cognitive proximity matrices, a cooperation effect is found when using the relational and technological ones. These results may suggest that the relational and technological preconditions for knowledge diffusion may be most effective when both the knowledge-generating region, as well as its partners (other regions linked by scientific relations and technological similarity), simultaneously commit recourses to innovative activities.

This result presents some striking similarities with the literature on ‘poverty traps’ (Azariadis, 1996); in fact, the need for a simultaneous wealth of local and lagged R&D intensity implies that even relevant local investments in absorptive capacity may fail to maximize the returns to local R&D, if other regions do not follow the same path. This result, in turn, suggests the presence of a path of absorptive capacity lock-in: regions which are surrounded by areas with low absorptive capacity, but insufficiently capable of absorbing knowledge, may fail to maximize the returns from their own R&D investment.56

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56 This set of estimates presents possible problems of endogeneity which may be difficult to rule out with full confidence. An indication of the resilience of the estimates comes from the relative stability of the most important parameter, viz. the absorptive capacity term, throughout all the estimates (but those based on social proximity). Further evidence may come from an instrumentation of the main estimates, which would, however, need credible instruments (possibly, time-lagged variables for each of the proximity measures here adopted). In Caragliu and Nijkamp (2012), this is done for the geographical proximity-based regressions.
A highly significant joint F test for all the estimates provides evidence of the strength of the empirical test.

4.6 Conclusions and policy implications
In this chapter we have adopted the analytical framework developed in Caragliu and Nijkamp (2012) and employed in finer spatial detail in Caragliu and Del Bo (2011) in order to provide additional insight into the nature of KSs, and the preconditions on the basis of which they are expected to travel. To this end, we presented a critical review of the traditional literature on different types of proximity, and provided an operational classification of these studies, which was employed to define five main types of proximities (geographical, relational, social, cognitive, and technological) capable of explaining KSs.

The empirical results show that the main findings of our previous studies hold. In particular, regional absorptive capacity is a crucial asset in order for regions to be able to attract knowledge generated in other areas. Along with absorptive capacity, a continuous effort of R&D from local actors is also conducive to attracting more knowledge.

However, some notable differences emerge when we consider the role of spatial lags of R&D effort. While geographically and cognitively distant regions exert a classical competition effect on the market for knowledge – more R&D commitments in other areas implies a reduction of the total knowledge absorption in each region – the same does not apply in the case of relational and technological proximity. In this case, instead, a cooperation effect emerges, whereby relational and technological preconditions for knowledge diffusion become more effective as both the knowledge-generating region, as well as its partners simultaneously commit recourses to innovative activities.

This last result points towards the emergence of ‘absorptive capacity clubs’, while knowledge-generating regions which aim to accumulate absorptive capacity, i.e. to invest over long time spans to accumulate local knowledge, may find it impossible to maximize the benefits of such investment, in the absence of surrounding regions with similar high levels of absorptive capacity. This is in particular true for the relational case, which suggests that, along with investing in R&D, policies should also aim at linking regions with intense innovation activity. This last point, however, poses a serious question about those regions that are simultaneously off major scientific cooperation networks, and are simultaneously poorly investing in R&D activities.

This possible trap should therefore be further investigated: one future research direction could be the analysis of the microfoundations of cooperation networks among regions, a topic which has recently received much scientific attention (see, for instance, Autant-Bernard et al., 2007, and Scherngell and Barber, 2009; 2011).

One major implication of this last point is the relevance of supra-regional coordination of policies. According to our empirical findings, regions must still invest in local R&D
accumulation in order to generate new knowledge. However, in the absence of similar efforts in other areas, such investment may provide sub-optimal outcomes. Even in a period of economic downturn, therefore, the need for regional innovation policies is now stronger than ever.

One additional research topic in the same line of research as ours would imply abandoning the use of a general knowledge measure, such as TFP, as the basis for our KS measure, and the choice of several different knowledge measures. Different types of knowledge may indeed travel on the basis of different preconditions, and our empirical approach may provide a first estimate of the relative importance of such diverse laws governing knowledge flows. Because of the interest of both academics and policy makers in the topic of KSs, and the rich nature of the spatial characteristics captured in the five types of proximity summarized here, further work on each of the four alternative definitions of proximity, apart from geographic proximity, would benefit our understanding of the mechanics of knowledge creation, diffusion, and absorption.

Empirically, this implies the creation of a long-term database of relational, social, technological and cognitive characteristics, linking pairs of regions and allowing the assessment of mutual knowledge flows. Moreover, a deeper insight into the different types of proximity identified here may provide a better understanding of the ensuing empirical results.

Finally, a relevant implication of our results lies in the crucial role of region-specific social, technological, cognitive and relational characteristics in shaping sound place-based policies (Barca, 2009; European Commission, 2011); without properly accounting for such properties, and for the interaction between them, any smart policy on regions in Europe is inevitably bound to fail.

References


Technical Appendix

1. Details on the raw indicators used for estimating the Knowledge Production Function

Table 26 Indicators and sources of raw data for the knowledge production function indicators

<table>
<thead>
<tr>
<th>Variable</th>
<th>Indicator</th>
<th>Source of raw data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Human capital</td>
<td>Percentage of labour force with ISCED 5 and 6 education</td>
<td>EUROSTAT</td>
</tr>
<tr>
<td>Growth of accessibility</td>
<td>Growth of multimodal accessibility</td>
<td>ESPON database</td>
</tr>
<tr>
<td>FDIs intensity</td>
<td>Count of FDI investments</td>
<td>Amadeus, raw data elaborated by Laura Resmini (Casi and Resmini, 2010)57.</td>
</tr>
<tr>
<td>Institutions</td>
<td>Regional quality of institutions</td>
<td>Charron et al. (2014)</td>
</tr>
</tbody>
</table>

2. Details of the social capital indicator

The results of the PCA performed in order to calculate social capital values in the EU27 regions are reported in Table 27 below. The social capital measure adopted here explains about 53 per cent of the total variance in the original data.

Table 27. Principal Component Analysis results for the four social capital indicators

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
</tr>
</thead>
<tbody>
<tr>
<td>Share of people participating in clubs and voluntary associations</td>
<td>0.26</td>
<td>0.96</td>
<td>-0.03</td>
<td>-0.02</td>
</tr>
<tr>
<td>Share of people participating in any social activity</td>
<td>0.62</td>
<td>-0.19</td>
<td>-0.05</td>
<td>-0.76</td>
</tr>
<tr>
<td>Share of people engaged in voluntary work</td>
<td>0.54</td>
<td>-0.16</td>
<td>-0.65</td>
<td>0.51</td>
</tr>
<tr>
<td>Share of people trusting other people</td>
<td>0.51</td>
<td>-0.10</td>
<td>0.76</td>
<td>0.39</td>
</tr>
<tr>
<td>Eigenvalue</td>
<td>2.12</td>
<td>0.92</td>
<td>0.69</td>
<td>0.27</td>
</tr>
<tr>
<td>Difference</td>
<td>1.20</td>
<td>0.23</td>
<td>0.42</td>
<td>-</td>
</tr>
<tr>
<td>Proportion</td>
<td>0.53</td>
<td>0.23</td>
<td>0.17</td>
<td>0.07</td>
</tr>
<tr>
<td>Cumulative</td>
<td>0.53</td>
<td>0.76</td>
<td>0.93</td>
<td>1.00</td>
</tr>
</tbody>
</table>

Source of raw data: European Values Study, Authors’ calculations

The first vector of the PCA, which summarizes more than half of the variance in the sample, is chosen as our measure of social capital. Regional variables are obtained by averaging out

individual responses to questions administered in connection with the European Values Study (EVS). The questions (for each domain within the social capital definition) put to a sample of European citizens are reported in Table 28.

Table 28. Selected questions in the EVS data set

<table>
<thead>
<tr>
<th>Domain</th>
<th>Question</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Community organizational</td>
<td>How often do you spend time in clubs and voluntary associations?</td>
<td>1 every week</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 once or twice a month</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 a few times a year</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 not at all</td>
</tr>
<tr>
<td>Engagement in public affairs</td>
<td>Do you participate in any form of social activity?</td>
<td>0-1</td>
</tr>
<tr>
<td>Community volunteerism</td>
<td>Do you take part in voluntary work in any community activity?</td>
<td>0-1</td>
</tr>
<tr>
<td>Informal sociability</td>
<td>Do you agree that “Most people can be trusted”</td>
<td>1 trust them completely</td>
</tr>
<tr>
<td></td>
<td></td>
<td>2 trust them a little</td>
</tr>
<tr>
<td></td>
<td></td>
<td>3 I neither trust nor distrust them</td>
</tr>
<tr>
<td></td>
<td></td>
<td>4 do not trust them very much</td>
</tr>
<tr>
<td></td>
<td></td>
<td>5 do not trust them at all</td>
</tr>
</tbody>
</table>

3. Details on the technological proximity matrix

Table 29 shows a list of the 2-digit manufacturing sectors whose location quotient has been calculated as a basis for identifying the technological distance matrix.

Table 29 NACE industries used in the calculation of the technological distance matrix

<table>
<thead>
<tr>
<th>Industry code</th>
<th>Industry name</th>
</tr>
</thead>
<tbody>
<tr>
<td>DA</td>
<td>Food, beverages and tobacco</td>
</tr>
<tr>
<td>DBDC</td>
<td>Textiles and leather, etc.</td>
</tr>
<tr>
<td>DFDGDH</td>
<td>Coke, refined petroleum, nuclear fuel and chemicals, etc.</td>
</tr>
<tr>
<td>DL</td>
<td>Electrical and optical equipment</td>
</tr>
<tr>
<td>DM</td>
<td>Transport equipment</td>
</tr>
<tr>
<td>OM</td>
<td>Other manufacturing</td>
</tr>
</tbody>
</table>

Source of raw data: EUROSTAT, Authors’ calculation.

58 EVS consists of a set of individual questionnaires administered to a sample of European citizens. Data have been collected in four waves: this chapter uses the 1999-2000 wave, as it is the first to comprehensively cover the regional dimension of the analysis. For more information on how the data set was collected, and details on its representativeness in terms of regional, sex, and age characteristics, see http://www.europeanvaluesstudy.eu/
4. Details on the cognitive proximity matrix

As Figure 21 shows, the formula adopted for calculating the cognitive proximity matrix implies that our indicator increases as the similarity of pairs of regions in patenting activity within 2-digit classes increases, while it decreases when regions share similar patenting profiles in 3-digit classes within each of the seven 2-digit classes. Variations within 2- and 3-digit classes are complementary, so that our indicator takes on higher values when regions are, indeed, neither too close nor too distant in patenting profiles (Figure 21).

Figure 21. Variety in the 2- and 3-digit classes and measure of inter-regional cognitive proximity

Source: Authors’ calculations.