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FULL ARTICLE

The geography of social capital and innovation in the European Union

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Abstract
This paper assesses the role of the associational activity dimension of social capital in regional innovation for 257 EU 28 regions in the pre-crisis (2000–2007) and the crisis (2008–2012) period. The analysis is carried out using flexible non-parametric kernel regressions, which allow for exploring heterogeneity across space and over time. The results show that effects widely differ across regions, but no differences are found between periods. In particular, the largest effects are found for less developed and transition regions from the periphery. In contrast, for most of the developed regions in the core of Europe the impact is non-significant. These results might be useful for policy design in the H2020 framework.

KEYWORDS
associational activity, European regions, innovation, social capital

1 | INTRODUCTION

A great deal of attention has been devoted in recent years to analyse the dynamics of regional innovation in Europe and its determinants. The geography of innovation is complex (Camagni & Capello, 2013), and regions in the enlarged European Union are highly heterogeneous. Therefore, one-size-fits-all approaches to foster innovation are far from ideal (Capello & Lenzi, 2013; Tödtling & Trippl, 2005), being necessary to understand that complexity for the design and implementation of innovation policies (Isaksen & Trippl, 2017). In particular, regional socio-economic and institutional conditions and the existence of some intangible assets such as human and social capital, the so-called 'social filter,' might affect the way in which knowledge is generated, transmitted and, ultimately, how it translates into aggregated output (Capello & Lenzi, 2014; Crescenzi & Rodríguez-Pose, 2011). Accordingly, following these authors, a better understanding of the processes underlying the creation of knowledge is crucial for the design of smart placed-based innovation strategies.

One potential driver of innovation is associational activity, in which this paper focuses. Associations are a particular form of the broader concept social capital which, according to Putnam's (1993) seminal work, can be defined as networks and shared norms that facilitate coordination and cooperation for mutual benefit.[1] In particular, associational life represents the network component of social capital, and it is measured as the rate of citizen's voluntary participation in different organizations and groups with data provided by the European Values Survey (EVS). Previous attempts in the literature have tried to unveil the associations-innovation link (see, for instance, Kaasa, 2009; Hauser, Tappeiner, & Walde, 2007), finding a positive effect as a general result.

However, the fact that regions are highly heterogeneous in terms of productive factors, socio-economic conditions and innovation patterns (Camagni & Capello, 2013; Isaksen & Trippl, 2017) has been largely overlooked and most of the previous literature failed to explore parameter heterogeneity, which should be the starting point for policy design. In this regard, recent evidence for the EU regions suggests that there are good reasons to rely on more flexible models able to deal with parameter heterogeneity. Peiró-Palomino (2016) found nonlinear and heterogeneous effects for associations on regional growth, while Sanso-Navarro and Vera-Cabello (2016) found analogous results for the case of innovation and growth. Similarly, we might expect regional effects of associations on innovation to differ.

Building on those recent findings, this paper attempts to contribute to the literature by revisiting the associations–innovation link in the EU regions from a flexible non-parametric perspective. Data-driven methods such as the kernel estimators proposed by Racine and Li (2004) allow the data to give their actual functional form. More interestingly, parameter heterogeneity in both the spatial and the temporal dimensions can be easily explored, since they provide observation-specific estimates.[2]

The study covers the period 2000–2012, which combines years of expansion (2000–2007) with crisis years (2008–2012). As argued by Filippetti and Archibugi (2011) and Archibugi, Filippetti, and Frenz (2013), investment in R&D dramatically reduced during the crisis, although the reduction was uneven across companies and regions. In that scenario of lower R&D investment, the role of associations could be more important to take advantage of the existent knowledge in the network and keep innovation levels. However, little is known about the role of associational activity during the crisis. The selected period enables us to address this question. If results differ, optimal policies should take into consideration the uneven effect of social features such as associational life not only across space but also over time.

The remainder of the paper is structured as follows. Section 2 provides a review of the literature. Section 3 introduces the methodology. Section 4 describes the sample, the data and provides some descriptive statistics. The results are reported in Section 5, and, finally, Section 6 concludes.

2 | SOCIAL CAPITAL, ASSOCIATIONAL ACTIVITY AND INNOVATION

As argued by Burt (2000), associations or connections between community members are identified as the network dimension of social capital. There are several positive externalities that have their origin in social networks, and we might expect them to generate a favourable environment for innovation. According to Storper (1995), knowledge is itself an ingredient of the community, embedded in its network. Therefore, interactions are crucial to understand innovation, as they enable connections, the sharing of information and the exchange of ideas (Dakhli & De Clercq, 2004; Malecki, 2012).

These arguments have their roots in the work by Granovetter (1973), who suggested that relationships between people can be either frequent contacts, featured by deep emotional involvement (friendship) or sporadic interactions with low emotional commitment (acquaintances). Whereas networks of the first type are characterized by strong ties, those of the second display weak ties. Considering these ideas, it is argued that strong friendship ties can hardly provide new information and knowledge, since individuals are likely to be similar and share alike values. In contrast,

[1] Many other definitions have been proposed in the literature, all closely related. See Malecki (2012) for an excellent review of social capital at the regional level.

[2] The popularity of these methods is on the rise, especially in the field of economic growth (see, for instance, Henderson, Papageorgiou, & Parmeter, 2012b, 2013 Sanso-Navarro & Vera-Cabello, 2015, 2016), and Peiró-Palomino (2016) for the particular case of social capital and growth.

associations are usually formed by acquaintances, which might provide access to new contacts and non-redundant knowledge. These networks are known as bridging networks. Following Granovetter's (1973) discussion, a bridge is formed by a line in the network which provides the only path between two agents. As individuals usually have several strong ties but valuable information for innovation flows through weak ties, eliminating weak ties is potentially more damaging for the transmission of new knowledge than removing strong ones. More recently, authors such as Boschma (2005) or Dettori, Marrocu, and Paci (2012) hold arguments in the same line, highlighting the importance of the weak links that define associations. As they argue, these ties are likely to be much more beneficial for innovation, as they connect heterogeneous agents, providing different types of information, preventing stagnation and enabling the emergence of boundary-spanning networks, which ultimately play an essential role in regional innovation.

Networks allow agents not only to be more informed about new ideas and developments, but also about the market singularities, available technologies and competitors. Beyond information, networks facilitate synergies through the combination of complementary thoughts, skills or even financial resources. In this regard, investing in innovative ideas has an inherent risk and the reputation of the inventor is important to obtain financial resources from investors (Rost, 2011). Therefore, inventors have incentives to be considered trustworthy and to maintain this status over time. Associations favouring interactions might be also beneficial for generating trust, which reduces opportunistic behaviour, increases credibility between parties in negotiations and limits information asymmetries (see Knack & Keefer, 1997). Investors are better informed and more secure about the actual value of the new innovative ideas, and this is accompanied by a reduction in monitoring costs, which ultimately translates into more projects financed (Bougheas, 2004).

An extensive list of empirical contributions at different levels of disaggregation corroborates the theoretical arguments given in this section. There are cross-country contributions such as Dakhli and De Clercq (2004), finding a positive relationship between associations and R&D expenditures. Similarly, Doh and Acs (2010) reported significant effects from associations to patenting activity. At the firm level, Landry, Amara, and Lamari (2002) focused on the effects of networks on both the likelihood and the radicalness of the innovation, finding a positive link. Ruef (2002) and Amara and Landry (2005) concluded that the ability of the entrepreneurs to obtain non-redundant information from social networks is essential for innovation. More recently, Boari, Molina-Morales, and Martínez-Cháfer (2017) showed that brokerage relationships based on interactions between firms are positive to foster innovation. Finally, at the regional level, Hauser et al. (2007) found that associations are the social capital dimension most strongly related to patenting activity in European regions. Nonetheless, the debate is still open, since other authors such as Kaasa (2009) reported greater effects for other social capital components, while still finding a positive effect for associations.

It is likely that regional heterogeneity can explain these mixed results. Regions differ in terms of economic, institutional and social conditions, and then the impact of associations might vary in intensity for different geographical settings. Also, the effects may differ under different policies and for distinct innovation patterns. In particular, social networks are more related to softer forms of innovation, although the effect is influenced by the regional context (Murphy, Huggins, & Thompson, 2016). Therefore, it is perfectly possible to find a non-significant effect for associations in particular locations. Then, as concluded by these authors, while some forms of social capital have been largely proved to impact innovation, they should not be considered as a panacea to increase innovation, as the effects can hardly be generalized.

3 | METHODOLOGICAL NOTES

3.1 | Non-parametric kernel regression

The nexus between associational activity and innovative performance is evaluated via non-parametric kernel regressions. As a preliminary approach, however, standard OLS parametric estimations are performed for a more direct comparison with the existent literature. The parametric equation takes the following form:

$$Y_i = \beta_0 + \sum_{j=1}^{J} \beta_j X_{ji} + \epsilon_i, \quad i = 1, 2, \ldots n, \tag{1}$$

where Y_i is the innovation performance for region i, X is a vector of J potential drivers of innovation and β_0 and β_j are parameters. As usual, ϵ_i represents the error term.

Parametric regressions are insightful, although they are subject to multiple and well-known assumptions (for example, the linearity of the parameters and the distribution of the errors). In contrast, non-parametric methods, data-driven in nature, relax these assumptions completely, providing a flexible framework. In this sense, Charlot, Crescenzi, and Musolesi (2014) considered similar methods to analyse innovation in EU regions, concluding that their main advantages rely on their capacity to deal with non-linear functional forms and parameter heterogeneity. The non-parametric counterpart to Equation 1 is given by:

$$Y_i = m(X_i) + \epsilon_i, \quad i = 1, 2, \ldots n, \tag{2}$$

where $m(.)$ represents an unknown smooth function capturing the conditional relationship between the dependent and the independent variables, which is directly derived from the data and may adopt multiple forms, either linear or non-linear. Therefore, if the underlying relationship between the variables is actually linear (as assumed in the parametric scenario), the non-parametric estimator will also reflect that feature. The rest of the elements in Equation 2 remain the same.

Parameters in Equation 2 can be estimated with different alternatives (see Henderson & Parmeter, 2015). In particular, the methods introduced by Racine and Li (2004) are becoming increasingly popular because of their attractive properties and, as a consequence, empirical applications in the field of economics have burgeoned in recent years (see Henderson et al., 2012b, 2013; Peiró-Palomino, 2016; Sanso-Navarro & Vera-Cabello, 2016). Following these contributions, we use the local-linear least squares (LLLS) estimator, based on 'generalized product kernels' and providing optimal estimates for mixed data sets with both continuous and categorical variables. For each sample point x_i, LLLS computes a weighted regression considering those observations near x_i, in which the standard assumptions of the parametric setting are unnecessary. Weights are given by a kernel function and a bandwidth vector such as that the observations in the proximity of x_i receive greater weights. Finally, $m(.)$ can be drawn after connecting all the individual estimations. These ideas can be formally expressed by reconsidering Equation 2 and adopting a first-order Taylor expansion for the continuous variables (x^c):

$$Y_i \approx m(x) + (x_i^c - x^c)\beta(x^c) + \epsilon_i, \tag{3}$$

where $\beta(x^c)$ is the partial derivative of $m(x)$ with respect to x^c. The LLLS estimator of $\delta(x) \equiv [m(x), \beta(x^c)]'$ adopts the form:

$$\hat{\delta}(x) = [X'K(x)X]^{-1}X'K(x)y, \tag{4}$$

where X is a n x $(q_c + 1)$ matrix with i row $(1, (x_i^c - x^c))$ and $K(x)$ is a n diagonal matrix of product kernel weighting functions. For the continuous variables a Gaussian kernel is selected, whereas for ordered categorical variables the choice is the Wang and Van Ryzin (1981) kernel. The LLLS estimator has desirable theoretical and applied properties and, as Henderson and Parmeter (2015) argue, it is preferable to other competing alternatives such as the local-constant least squares (LCLS). Besides being more accurate in its computation of the conditional mean, LLLS allows for the estimation of the first derivatives, that is, the gradients or 'partial effects.'

Bandwidth selection is crucial when using non-parametric methods, since bandwidths determine the amount of observations considered in each partial weighted regression. Following recent practice in the literature, they are chosen using the least-squares cross validation (LSCV) method (see Henderson & Parmeter, 2015). Moreover, the bandwidths provide useful information on the linearity of the estimated parameters when applying LLLS. In particular, when a bandwidth for a given regressor is larger than its upper bound (UB), it indicates linearly for that variable. Upper bounds are defined as two times the standard deviation for continuous variables and as the unity for categorical ordered variables.

Apart from its flexibility, the LLLS estimator has other interesting properties. One of them is that it provides observation-specific estimates, which means that a complete evaluation of the effects of a given regressor is possible in both the spatial and the temporal dimension. For instance, *ex post* groups can be formed of regions sharing similar characteristics such as income levels, and the analysis can also be made in different time periods. Furthermore, the estimator is robust to spatial dependence, which is one of the major issues when dealing with regional data. The European context is not an exception, and the importance of spatial effects has been highlighted in studies such as Basile (2008), Crespo Cuaresma and Feldkircher (2012) or, more directly related to innovation, Moreno, Paci, and Usai, (2005). According to McMillen (2010, 2012) and Sanso-Navarro and Vera-Cabello (2015), the LLLS estimator might deal with spatial dependence better than parametric spatially weighted regressions. The explanation lies in the nature of the estimator, which makes it consistent and asymptotically normal under the existence of spatial dependence with no need to specifically control for it. As commented above, LLLS uses different local samples of neighbouring observations to run a local weighted regression for each sample point, capturing the local singularities of the data. Whereas physical distance is a measure of proximity, there are many other possibilities such as the cognitive, the social or the institutional distance (see Boschma, 2005). In fact, recent papers in the literature of spatial econometrics such as Caragliu and Nijkamp (2016) define spatial matrixes based on those attributes. Those features are expected to be highly correlated with physical distance. Given these arguments, as long as the LLLS considers as neighbouring regions those similar in terms of both the dependent and the independent variables, the spatial dependence is likely to be endogenously captured.

Finally, as a robustness check, we perform Hsiao, Li, and Racine (2007) tests for correct model specification. The tests compare the parametric specification against the non-parametric counterpart, establishing which one is preferable given the structure of the data. If the null hypothesis ($H0 \; : \; Pr[E(x|z) \; = \; f(z, \beta)] \; = \; 1$) cannot be rejected, the parametric linear model is preferred. In contrast, under the alternative ($H1 \; : \; Pr[E(x|z) \; = \; f(z, \beta)] \; < \; 1$) the non-parametric specification better captures the underlying relationship.

3.2 | Non-parametric regression with endogenous regressors

Endogeneity is a major concern in regression analysis and its sources can be manifold. One of them is reverse causality and, in that regard, the theory revisited along the paper suggests that the relationship goes from associations to innovation. Most social values are passed on from one generation to the next and remain remarkably stable over time.[3] Apart from the stability argument, and in order to deal with reverse causality, associational activity is measured at the beginning of the period whereas the dependent variable, innovation performance, is the average value of the entire period.

Another source of endogeneity are omitted variables. Drawing on the growth literature, Brock and Durlauf (2001) acknowledged the difficulty of capturing all the relevant growth regressors, whereas Durlauf (2002) concluded that most of the cross-country growth regressions fail to incorporate all the relevant growth determinants. Similar arguments apply for the innovation literature, where there is no consensus on a benchmark model. In this respect, the inclusion of fixed effects should minimize this problem.

Despite the above precautions, for further robustness an instrumental variables (IV) approach is implemented considering the Su and Ullah (2008) methodology, suitable for dealing with endogenous variables in kernel regressions.[4] Let us reconsider Equation 2, but now with a single endogenous regressor b. Then the model is defined as:

$$Y_i = m(X_i, b_i) + \epsilon_i, \quad i = 1, 2, ...n, \tag{5}$$

[3] Uslaner (2008) and Nunn and Wantchekon (2011) showed that particular forms of social capital such as social trust are inherited from generation to generation. Similarly, Bjørnskov (2012) and Bjørnskov and Méon (2013) argued that trust levels remained stable at least since the Second World War. Although no previous studies focus on the roots of associational activity, these arguments might also apply for it, since both are social capital dimensions that refer to well ingrained behavioural and cultural aspects.

[4] Its interesting properties have led to its selection in recent empirical applications such as Henderson et al. (2013) and Peiró-Palomino (2016). Other alternative proposals in the non-parametric framework are those by Newey and Powell (2003), Horowitz (2011) or Darolles, Fan, Florens, and Renault (2011).

with

$$b_i = n(L_i) + \omega_i, \quad i = 1, 2, \ldots n, \tag{6}$$

where L_i in Equation 6 is a vector of instruments, $n(.)$ is an unknown smooth function and ϵ_i and ω_i are error terms. The other components in both Equations 5 and 6 are common to Equation 2.

The IV estimation is performed in two stages. In the first one, a LLLS regression is run where the dependent variable is the endogenous variable and the instruments are the explanatory variables. The second stage consists of estimating the original model including both the exogenous and the endogenous regressors, together with the residuals from the first stage.

4 | EMPIRICAL FRAMEWORK AND DESCRIPTIVE STATISTICS

This section introduces the sample, the data, their sources and some descriptive statistics. The sample includes 257 NUTS 2 regions of the EU 28 countries. It fails to include all the EU NUTS 2 because of data constraints. A popular solution is the use of mixed samples of NUTS 1 and NUTS 2 regions, although there is some controversy on which level is preferred for regional analysis (see Basile, 2008). In this paper NUTS 2 was selected because these regions are the units of analysis for applying EU regional policies. Furthermore, most of the studies on regional innovation are carried out at that level. The number of NUTS 2 varies from one country to another. For example, whereas small countries such as Latvia or Malta consist of a single NUTS 2 region, others such as Germany or the UK have more than thirty. The study covers the period 2000–2012, which is subdivided in two shorter subperiods to analyse whether the relationship of interest is affected by the crisis. The first, 2000–2007, corresponds to economic expansion years. The second, 2008–2012, covers the crisis years. As data correspond to either the average (the dependent) or the value in the first year of each period (the independent), there are two observations per region, totalling 514 observations.

4.1 | Innovation

Following common practice in the previous literature (see, for example, Akçomak & Müller-Zick, 2015; Akçomak & Ter Weel, 2009; Crescenzi & Rodríguez-Pose, 2013; Rodríguez-Pose & Crescenzi, 2008; Sanso-Navarro & Vera-Cabello, 2016), we consider an indicator of the outcomes of the innovation efforts, namely the number of patents per million inhabitants (in logs), provided by the European Patent Office (EPO). The EPO classifies patents according to the residence of the inventor and, in cases of more than one inventor, each region receives a proportional quota.

Some descriptive statistics are provided in Table 1, which shows remarkable regional disparities. The left panel in Figure 1 displays violin plots, considering average data for each subperiod. These are boxplots overlaid by a density function. A marked bimodality is observed in both periods. The main bump is slightly above the median value (represented by the white point inside the boxplot), and a smaller second mode, grouping regions with poor innovation outcomes emerges on the left, far below the median. Even though the main features of these described distributions remain essentially unaltered over time, some subtle changes are observable. Specifically, the left tail is shorter in the crisis period and the second mode has slightly shifted closer to the main one.

Complementarily, the left panel in Figure 2 displays the average regional innovation intensity for the entire period.[5] Innovation is mostly concentrated in regions from Germany, Austria, the Netherlands, North of Italy, South of the UK and the Nordic countries. Some French regions, the regions of Catalonia and the Basque Country in Spain together with the Irish regions have intermediate levels, whereas the lowest performance is found among the new EU members, Portugal and in most of the regions from Greece, Cyprus and the South of Spain and Italy.

[5] Given that the violin plots for the two periods do not show important differences, maps with the average score are also informative.

TABLE 1 Descriptive statistics (2000–2012)

Variable	Obs.	Mean	s.d.	1st quartile	Median	3rd quartile	Min.	Max.
Patents (logs)	514	3.647	1.700	2.275	4.108	4.920	−1.570	6.651
Associational activity	514	3.342	3.136	1.549	2.490	4.400	0.000	23.958
R&D expenditure	514	1.332	1.317	0.483	0.975	1.680	0.000	12.190
Education	514	21.639	8.509	15.100	21.250	27.700	5.400	48.900
GDP *per capita* (logs)	514	9.958	0.436	9.777	10.026	10.229	8.434	11.455
Primary sector	514	3.391	3.453	1.084	2.327	4.410	0.002	18.848
Industrial sector	514	22.520	7.819	16.939	22.622	27.407	3.304	54.459
Infrastructures	514	29.802	30.870	9.000	23.000	37.000	0.000	222.000

Notes: Figures are averages of the two selected periods (2000–2007) and (2008–2012). For the dependent variable (patents), the mean value of each subperiod is considered. The rest of variables are measured in the first year of each subperiod, namely years 2000 and 2008, respectively.

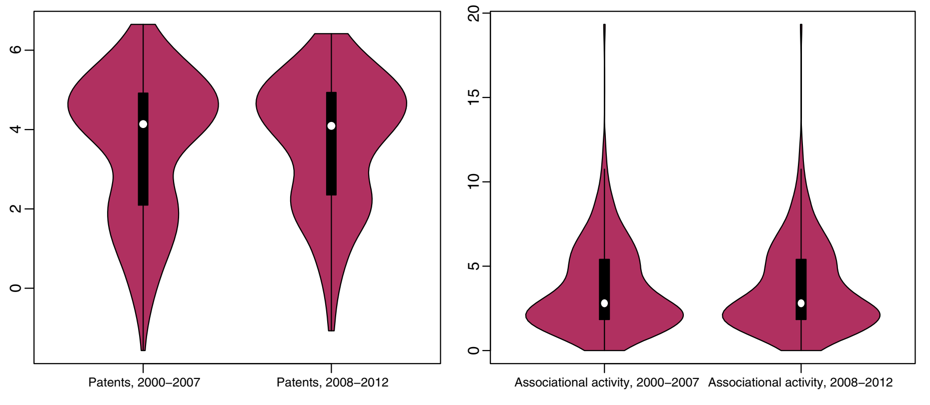


FIGURE 1 Violin plots, patents and associational activity by period

4.2 | Associational activity

As commented on in this paper, the associational dimension of social capital is considered. In comparison with other social capital domains, in the European context larger impacts are found for associational activity on economic outcomes in general (see Beugelsdijk & Van Schaik, 2005; Peiró-Palomino, 2016) and on innovation in particular (Hauser et al., 2007). The variable selected corresponds to active (voluntary) participation in a wide range of associations.[6]

Data on active associational activity are provided by the European Values Study (EVS). This survey, conducted for four different waves (years 1981, 1990, 1999 and 2008) contains information on a wide range of social values and individual beliefs. Data were taken from the two latter waves, corresponding with the two subperiods analysed. In addition, these waves coincide with the initial years of the periods, which might help to alleviate endogeneity issues.[7] The variable is defined as the percentage of respondents who actively participate in one or more of the following associations: i) welfare organization; ii) religious organization; iii) cultural activities; iv) trade unions and political parties; v) local community action; vi) development/human rights; vii) environment, ecology; viii) professional associations; ix) youth

[6]The related literature distinguishes between mere participation and active enrolment. The latter is considered to be a better proxy, since an individual can be enrolled in an association but not take part in any group activity. This is why, according to Bjørnskov (2006), active participation is preferable to simple membership. In addition, empirical studies such as Beugelsdijk and Van Schaik (2005) find that active enrolment has the largest effect on economic performance and recent analyses in the same context (see Dettori et al., 2012; Forte, Peiró-Palomino, & Tortosa-Ausina, 2015; Peiró-Palomino, 2016) corroborate its significance.
[7]In any case, and instrumental variables estimation is performed for further robustness.

(a) Patents, 2000–2012 **(b)** Associational activity, 2000–2012

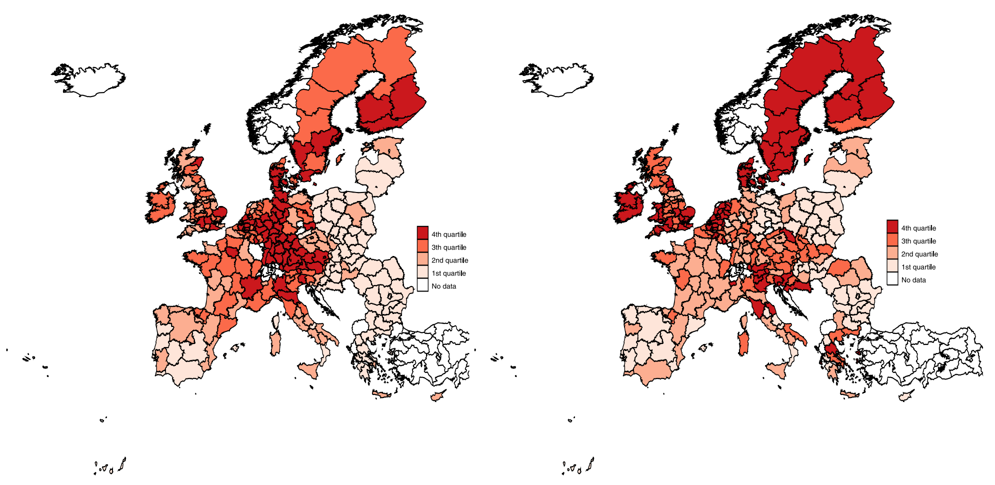


FIGURE 2 Regional distribution of patents and associational activity

work; x) sports/recreation; xi) women's groups; xii) peace movement; xiii) voluntary health; and xiv) other groups. It is constructed by aggregating individual responses in the survey.

The EVS 1999 has some data constraints. For example, it does not provide data for Malta and for Denmark, Germany, Ireland, France and the UK the maximum level of regionalization is NUTS 1 level. For these cases, all regions belonging to the same NUTS 1 are assumed to share the same level of associationism.

For the case of Malta, data from EVS 2008 is used for both periods. In addition, as no information for our variable is available in the EVS 2008 for the Italian regions, information from the EVS 1999 was used for both periods. Table 1 reports summary statistics, while the right panel in Figure 1 displays violin plots by period. They are virtually identical, corroborating the stability of associational activity. They show one main mode in the interval (0–5), a smaller second mode above that range and a long right tail containing the regions with the highest associational levels.

The right panel in Figure 2 displays the map for associational activity, considering average data from EVS 1999 and 2008. It shows the highest level of associational activity for regions in Finland, Sweden, Denmark and the Netherlands, as well as Ireland and the South of the UK. Relatively high levels are held by some Central European countries such as Hungary, Slovakia, the Czech Republic and some Italian regions. Some of the Spanish and Bulgarian regions together with France, Latvia and Estonia have intermediate scores. The lowest levels are in the majority of Portuguese, Spanish, Polish and Romanian regions.

4.3 | Control variables

A set of regional controls is included considering recent contributions on related issues (see Crescenzi & Rodríguez-Pose, 2013; Echebarria & Barrutia, 2013; Rodríguez-Pose & Crescenzi, 2008; Sanso-Navarro & Vera-Cabello, 2016). The most immediate is the innovation effort, measured by R&D expenditure as a percentage of GDP. Human capital is also accounted for, measured as the percentage of population aged between 25 and 65 with tertiary studies. Regional wealth might also determine the capacity of one region to innovate. It is proxied by GDP *per capita* (in PPS). The nature of the regional productive structure is captured by two variables: (i) gross value added (GVA) of the primary sector (agriculture, forestry and fishing) as a share of total GVA; and (ii) GVA of the industrial sector as a share of the total GVA. Finally, regional infrastructure is measured by the density of motorways (kilometres per thousand square kilometres). All the data for the control variables come from Eurostat, and all these are measured in the first year of each period, that is, years 2000 and 2008 for the first and second period, respectively, in order to alleviate reverse causality problems as far as possible. Table 1 provides descriptive statistics for all of them, referring to the entire period (average value of 2000 and 2008).

4.4 | Instrumental variables

Finding appropriate instruments is a challenge. Contributions at the country level in the related literature such as Tabellini (2010), Bjørnskov (2010) and Bjørnskov and Méon (2013) have mostly relied on geographical and linguistic data to instrument social capital variables. At the regional level, Akçomak and Ter Weel (2009) considered historical education levels. The main difficulty in this paper is the nature of the sample, which includes regions from Western and Eastern European regions, with severe data constraints for the latter.

Following Peiró-Palomino (2016), built on a very similar sample, associational activity is instrumented by (i) regional latitude; (ii) historical universities; and (iii) pronoun-drop characteristic in language. Bjørnskov and Méon (2015) instrumented country level social trust with the minimum temperature in the coldest month of the year. For the regional case latitude is preferred for reasons of availability.[8] As Bjørnskov and Méon (2015) argue, temperature and culture are historically related, since in the coldest areas collaboration with one's community was essential to survive the winters. A dummy variable controls for the existence of a university in 1850. Akçomak and Ter Weel (2009) also used universities as an instrument. As centres of culture and knowledge diffusion, their role in modelling society's beliefs and culture might be important. Cowan (2005) suggests universities are a public good that strengthens social cohesion. They generate not only graduates, but also more participant citizens in the public sphere (Akçomak & Ter Weel, 2009). Finally, a country level dummy controls for the 'pronoun-drop feature' in the country's predominant language. Bjørnskov and Méon (2015) describe how the preservation of the personal pronoun reflects higher respect for the individual and the individual's rights, leading to societies with higher social capital.[9]

The three instruments are either predetermined or historical, and they are expected to have influenced regional cultural patterns such as the tendency to enrolle in associations. However, their correlation with current levels of innovation is implausible, which makes them good candidates.

5 | EMPIRICAL RESULTS

This section contains the estimation results. Different models were estimated, where the variables defined in Section 4 are included sequentially. In all the models the dependent variable is the average number of patents per million inhabitants (in logs), as defined in the preceding section. Model 1 is a simple regression, including associational activity only. Model 2 adds the controls of R&D expenditures and education. Model 3 builds on model 2 with GDP *per capita* (in logs), the sector variables (primary and industrial sector) and the infrastructures. Model 4 is the most comprehensive. It adds the temporal effects (the two periods considered) and country fixed effects, the latter capturing common features at the country level such as institutional quality, R&D policy or features of the educational system.[10]

5.1 | Results for the full sample

Parametric ordinary least squares estimations for models 1–4 are reported in Table 2. The coefficients are in all cases significant and have the expected positive sign, aligned with previous findings such as Hauser et al. (2007), and with

[8] Latitude and temperature are highly correlated.

[9] Bjørnskov and Méon (2015) use this instrument for social trust. As both social trust and associational activity are social capital indicators–generally where one is high the other is high too (Peiró-Palomino, 2016)–we consider the pronoun-drop feature as a suitable instrument.

[10] Although a panel fixed-effects model would be, a priori, a more suitable strategy, some difficulties prevent us from estimating it. Panel data techniques, and in particular the fixed effects estimator in the non-parametric framework are still in the initial stages of development, and as such are not easily implemented (Henderson & Parmeter, 2015).

TABLE 2 Ordinary least squares estimates

	Dependent variable: Patents (logs)			
Variables	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Intercept	3.138***	1.129***	−19.833***	−10.460***
	(0.105)	(0.159)	(0.259)	(1.283)
Associational activity	0.152***	0.111***	0.048***	0.014*
	(0.022)	(0.018)	(0.012)	(0.008)
R&D expenditure		0.485***	0.273***	0.122***
		(0.047)	(0.032)	(0.021)
Education		0.069***	0.013**	0.024***
		(0.007)	(0.005)	(0.006)
GDP *per capita* (logs)			2.205***	1.414***
			(0.139)	(0.130)
Primary sector			−0.080***	−0.024**
			(0.015)	(0.011)
Industrial sector			0.041***	0.031***
			(0.005)	(0.003)
Infrastructures			0.001	0.000
			(0.001)	(0.000)
N	514	514	514	514
R^2 (*Adjusted*)	0.077	0.442	0.749	0.914
F_{STAT}	43.85***	136.90***	219.90***	161.80***
Country effects	No	No	No	Yes
Temporal effects	No	No	No	Yes

Notes: Standard errors are in parentheses. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively. Country effects control for country level characteristics. Time effects control for common features in the two periods of analysis (2000–2007) and (2008–2012).

more general studies on social capital (various dimensions) and growth such as Beugelsdijk and Van Schaik (2005), Akçomak and Ter Weel (2009), Forte et al. (2015) and Peiró-Palomino (2016). Their magnitude range from 0.15 (model 1) to 0.014 (model 4), decreasing after controlling for other innovation determinants, especially education and GDP *per capita*, which may be capturing part of the effect. The results for the rest of control variables are also in line with the theory and remain relatively stable through the different specifications. Regional GDP *per capita* is also positive, showing that the income level of a region might condition its innovative performance.[11] The composition of the economic fabric also has a non-negligible effect. More primary sector-based economies are less innovative, whereas those with a more predominant industrial sector perform better in terms of innovation. The infrastructures variable, however, is non-significant in the two models where it is included. All models are jointly significant and the adjusted R^2 is quite high in all four. As expected, model 4 explains the most variability of the dependent variable, and is selected for the additional results shown in the next subsection 5.2.

Results for the nonparametric counterparts, estimated via LLLS are provided in Tables 3 and 4. The former contains the upper bounds for all the variables, the estimated bandwidths, and the Hsiao et al. (2007) tests for correct model specification, while the latter reports quartile estimates for all the variables in models 1–4. Note that all the bandwidths are below the upper bounds in models 1–3, which indicates that the variables enter the model non-linearly. Once time and country fixed effects are incorporated in model 4, some of them become linear, including the variable of interest. The control variables R&D expenditure, education and the economic fabric indicators enter non-linearly. In

[11]We acknowledge that the relationship might run in the opposite direction. This is why models not including GDP *per capita* (Models 1 and 2) were estimated. The results for associational activity remain qualitatively unaltered although, as expected, quantitative differences in the estimations are observed.

TABLE 3 Local linear least squares, bandwidths and model specification tests (Hsiao et al., 2007)

	Dependent variable: Patents (logs)				
Variables	**UB**	**Model 1**	**Model 2**	**Model 3**	**Model 4**
Associational activity	6.271	0.313	1.467	3.201	**10.398**
R&D expenditure	2.634		0.545	1.079	1.474
Education	17.018		6.589	6.421	**6,313,481**
GDP *per capita* (logs)	0.871			0.287	**1,944,899**
Primary sector	6.906			2.419	6.249
Industrial sector	15.638			5.836	7.288
Infrastructures	61.740			24.796	**80.172**
Country	1.000				0.069
Time	1.000				**0.999**
Jn-statistic		18.554	26.117	13.103	8.298
		(0.000)	(0.000)	(0.000)	(0.000)

Notes: Bandwidths are computed using least squares cross validation (LSCV). A bandwidth in bold indicates that it exceeds the upper bound (UB). In LLLS estimations it indicates that the regressor enters the model linearly. The *Jn*-statistic provides the result for non-parametric Hsiao et al. (2007) tests of correct functional form. The null hypothesis being tested is whether the parametric specification is correct ($H0 : Pr[E(x|z) = f(z, \beta)] = 1$), against the alternative that it is not ($H1 : Pr[E(x|z) = f(z, \beta)] < 1$). Bootstrap (399 repetitions) p-values are in parenthesis.

all four models, however, the null hypothesis of correct specification of the Hsiao et al. (2007) tests is strongly rejected, indicating that assuming linearity the models are misspecified.

Much more insightful are the estimated partial effects, reported in Table 4. Considering that non-parametric regression provides observation-specific estimates, the table reports quartile estimates from the full vector of estimated partial effects, together with their corresponding bootstrap standard errors (wild bootstrap) (see, for computation details, Henderson & Parmeter, 2015).[12] The R^2 is always higher than in the parametric estimations, since non-parametric methods are known for their ability to fit the data. The results for associational activity show a sizeable variability between quartiles, aligned with Peiró-Palomino's (2016) results for the case of associations and growth, and supporting theoretical arguments in the literature highlighting regional heterogeneity (Capello & Lenzi, 2014), calling for smart specialization and region–specific strategies for innovation. In all four models, the second and the third quartiles are significant, but the first one is not in any of the cases. The control variables behave according to the theory, but they also show great variability. For the sake of comparison with the parametric scenario, let us focus on the most comprehensive model 4, on which the main conclusions are based and for which the widest range of results are provided.[13] Note that in the parametric case (Table 2) the average coefficient is 0.014, only weakly significant (10%). Nevertheless, the non-parametric estimation yields significant coefficients of 0.031 and 0.085 for some regions, corresponding to the second and third quartiles. This suggests that the actual effect in some regions is far from the average prediction estimated via OLS.

In order to report all the estimated coefficients, distinguishing also by period, kernel densities and 45° plots are displayed in Figure 3. The first panel in the figure superimposes the three densities, showing that the estimated effects do not reveal notable variations over time. Most of the observations concentrate around a main mode on the positive side, with a secondary mode around 0.2 containing regions where effects are greater. Table 5 reports results for the Li (1996) tests for the comparison of kernel distributions; the null hypothesis of equality could not be rejected. The associated 45° plots, introduced by Henderson, Kumbhakar, and Parmeter (2012a), represent all the estimates (black bullets)

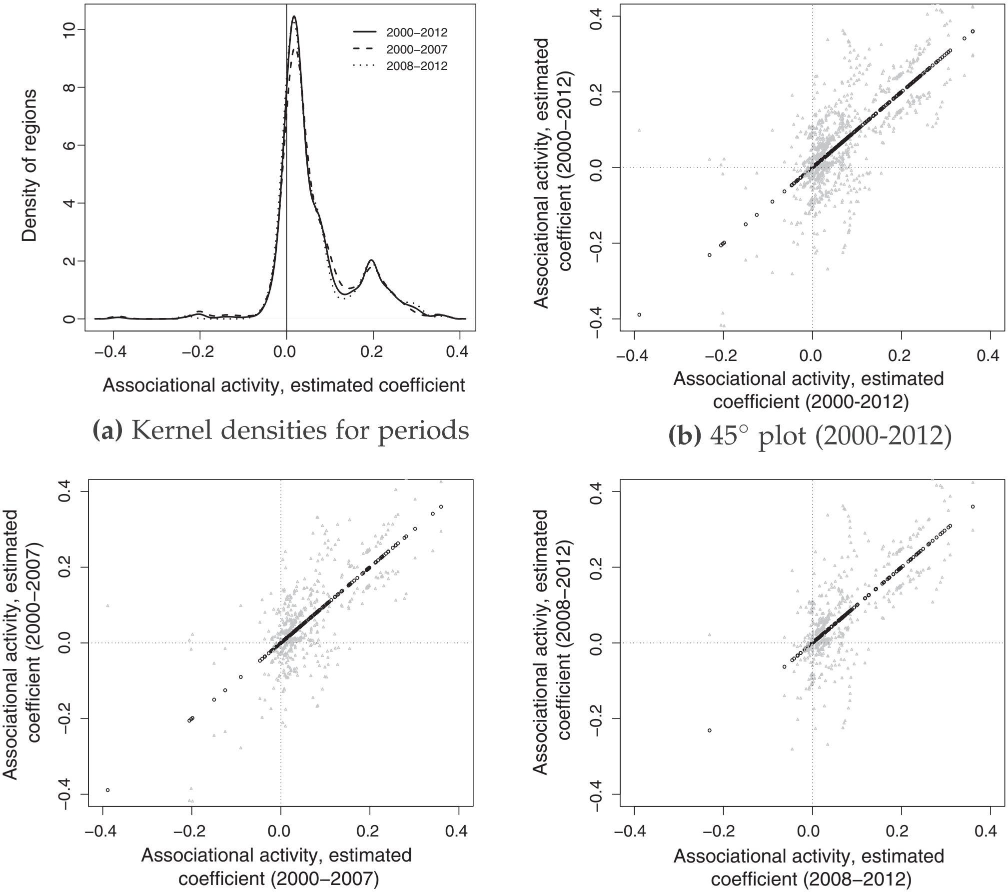
[12] Bootstrap standard errors are preferable for robustness reasons to the asymptotic ones, since the sample size is relatively small.

[13] For reasons of space, all the results cannot be included in the paper. Note that the non-parametric regression yields a region-specific effect (gradient or partial effect) for each variable in each model and for each period. This explains why only the non-parametric estimates for the most comprehensive model are reported.

TABLE 4 Local linear least squares, quartile estimates for the continuous regressors

	Dependent variable: patents (logs)											
	Model 1			Model 2			Model 3			Model 4		
Variables	**Q1**	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**	**Q1**	**Q2**	**Q3**
Associational activity	−0.378	0.196	0.990***	0.064	0.294***	0.507***	0.015	0.077***	0.146***	0.010	0.031***	0.085***
	(0.450)	(0.552)	(0.311)	(0.048)	(0.039)	(0.041)	(0.052)	(0.017)	(0.040)	(0.118)	(0.011)	(0.039)
R&D expenditure				0.665***	1.268***	1.757***	0.388***	0.518***	0.669***	0.237***	0.321***	0.608***
				(0.123)	(0.118)	(0.066)	(0.045)	(0.050)	(0.097)	(0.102)	(0.163)	(0.116)
Education				0.001	0.045***	0.097***	−0.024***	0.001	0.024	−0.030***	0.000	0.026*
				(0.009)	(0.007)	(0.006)	(0.006)	(0.004)	(0.017)	(0.007)	(0.010)	(0.016)
GDP *per capita* (logs)							1.118***	1.731	2.494***	1.001***	1.584***	2.414***
							(0.286)	(1.250)	(0.238)	(0.269)	(0.129)	(0.185)
Primary sector							−0.120***	0.006	0.013	−0.097***	0.000	0.009
							(0.024)	(0.026)	(0.098)	(0.037)	(0.065)	(0.027)
Industrial sector							0.017***	0.039***	0.058***	0.018***	0.036***	0.063***
							(0.007)	(0.003)	(0.021)	(0.006)	(0.007)	(0.015)
Infrastructures							0.002	0.006**	0.013***	−0.003***	0.000	0.009***
							(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)
N	514			514			514			514		
R^2	0.250			0.717			0.940			0.977		
Country effects	No			No			No			Yes		
Temporal effects	No			No			No			Yes		

Notes: Estimates correspond to first (Q1), median (Q2) and third (Q3) quartile of the vector of partial effects for each regressor, considering that the rest of variables in the model remain constant at their median value. Wild bootstrap standard errors are in parenthesis. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively. Country effects control for country level characteristics. Time effects control for common features in the two periods of analysis (2000–2007) and (2008–2012).



(a) Kernel densities for periods

(b) 45° plot (2000-2012)

(c) 45° plot (2000-2007)

(d) 45° plot (2008-2012)

FIGURE 3 Estimated coefficients for associational activity in model 4

and their associated 95% confidence bands (grey triangles), which is useful to visualize at a glance the significance of the observations.[14] The results are represented for the whole period, and for the two separate subperiods, since LLLS yielded two estimates per region, one for the first period and another for the second. The 45° plots show that most of the negative coefficients are not significant, as well as most of the estimates in the vicinity of zero. Therefore, the estimation corroborates the general positive link between associational activity and innovation, although with varying effects across regions. However, the effects are similar for both expansion and crisis periods.

Finally, we provide results accounting for the endogeneity of associational activity. As explained in subsection 3.2, the potentially endogenous variable is regressed in a first stage on the three instruments described in subsection 4.4 and the residuals from that regression are added as an additional regressor in the second stage. Table 6 reports quartile estimates, and enables direct comparison to the original model 4.[15] The original (non-IV) quartile estimates are in columns (2)–(4), while columns (5)–(7) correspond to the instrumented counterpart. Only quantitative changes are observed when endogeneity of associations is explicitly accounted for. The estimated coefficients for the variable of interest and the degree of heterogeneity increase, reinforcing the above conclusions. In any case, endogeneity is always

[14] Note that if the zero is contained in the bands, that estimate is not significant.

[15] The IV estimation was only performed for model 4, from which the main conclusions are extracted. Note that the model includes country fixed effects and time effects, limiting the possibility of endogeneity coming from unobserved variables.

TABLE 5 Non-parametric comparison (Li, 1996) of the estimated densities for different groups in Model 4

Compared distributions	t-statistic
Full sample, (2000–2012) vs. (2000–2007)	−0.340
Full sample, (2000–2012) vs. (2008–2012)	−1.272
Full sample, (2000–2007) vs. (2008–2012)	0.756
Less developed regions vs. transition regions	13.435***
Less developed regions vs. more developed regions	45.624***
Transition regions vs. more developed regions	2.361***
Less developed regions, (2000–2007) vs. (2008–2012)	0.045
Transition regions, (2000–2007) vs. (2008–2012)	1.617*
More developed regions, (2000–2007) vs. (2008–2012)	−0.056

Notes: Under the null hypothesis ($H0 : h(x) = g(x)$), the two distributions are equal. Under the alternative ($H1 : h(x) \neq g(x)$), they differ statistically. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively.

a difficult issue to deal with, and even the precautions taken (measurement strategy to avoid reverse causality, inclusion of country and time fixed effects to control for unobserved effects and instrumental variables estimation) results should be interpreted carefully.

5.2 | Results for regions at different levels of development

Given that the results for the full sample are highly heterogeneous, this section explores the effects for particular groups of regions similar in terms of development. Following the classification of the EU Cohesion Policy in the H2020 framework, regions were grouped into three categories: (i) 'more developed regions' (with GDP *per capita* over 90% of the EU average); (ii) 'transition regions' (between 75% and 90%); and (iii) 'less developed regions' (below 75%). These groups were made a posteriori.[16]

Considering the findings by Knack and Keefer (1997), suggesting that the trust dimension of social capital is more important for poor economies,[17] it seems pertinent to analyse whether the effects of associations vary for poor and rich economies. Moreover, and similarly to the case of R&D efforts, innovation and growth (see Capello & Lenzi, 2014; Sanso-Navarro & Vera-Cabello, 2016), we might expect the impact of associations to vary across regions, since they do not only differ in terms of GDP *per capita*, but also in their production factors, socio-economic conditions and innovation patterns (see the arguments in Camagni & Capello, 2013; Isaksen & Trippl, 2017) and empirical papers such as Peiró-Palomino (2016), finding parameter heterogeneity for a variety of social capital indicators, including associations.

To summarize the results, Table 7 reports median estimates, also distinguishing by period, whilst the more informative Figure 4 plots the entire distribution of partial effects. The results for the entire period yield a similar coefficient for the less developed and transition regions, and much smaller for the more developed regions. Although it is not possible to compare these results to previous literature, they are in line with Knack and Keefer's (1997) findings.[18] Considering the median estimate for the entire period, the effect for less developed regions is twice as large as that for the more developed. Therefore, more associational activity in those regions represents an opportunity for them to catch up with the more developed ones. The first quadrant in Figure 4 displays the densities. Li (1996) tests in Table 5 reject the null hypothesis of equality of distributions in all cases. The most remarkable feature is that effects are much more similar

[16] That is, results do not come from separate estimations, but correspond to partial effects extracted from the original Model 4 and grouped according to the development level.
[17] The authors suggested that social capital provides an informal framework that guarantee economic transactions in poorly developed legal systems.
[18] Note that the effects cannot be directly comparable, since Knack and Keefer (1997) focused on trust and not on associations.

TABLE 6 Instrumental local linear least squares (Su & Ullah, 2008), quartile estimates for the continuous variables in Model 4

Variables	Dependent variable: patents (logs)					
	Model 4			IV Model 4		
	Q1	Q2	Q3	Q1	Q2	Q3
Associational activity	0.010	0.031***	0.085***	−0.027	0.078**	0.305***
	(0.118)	(0.011)	(0.039)	(0.027)	(0.038)	(0.051)
R&D expenditures	0.237***	0.321***	0.608***	0.075	0.266***	0.485***
	(0.102)	(0.163)	(0.116)	(0.064)	(0.060)	(0.148)
Education	−0.030***	0.000	0.026*	−0.022**	0.009	0.044***
	(0.007)	(0.010)	(0.016)	(0.010)	(0.010)	(0.014)
GDP *per capita* (logs)	1.001***	1.584***	2.414***	1.131***	1.611***	2.307***
	(0.269)	(0.129)	(0.185)	(0.449)	(0.246)	(0.388)
Primary sector	−0.097***	0.000	0.009	−0.073	0.000	0.010
	(0.037)	(0.065)	(0.027)	(0.083)	(0.023)	(0.073)
Industrial sector	0.018***	0.036***	0.063***	0.022	0.045**	0.060***
	(0.006)	(0.007)	(0.015)	(0.018)	(0.019)	(0.005)
Infrastructures	−0.003***	0.000	0.009***	−0.003	0.000	0.010***
	(0.001)	(0.002)	(0.002)	(0.011)	(0.003)	(0.073)
N	514			514		
R^2	0.977			0.989		

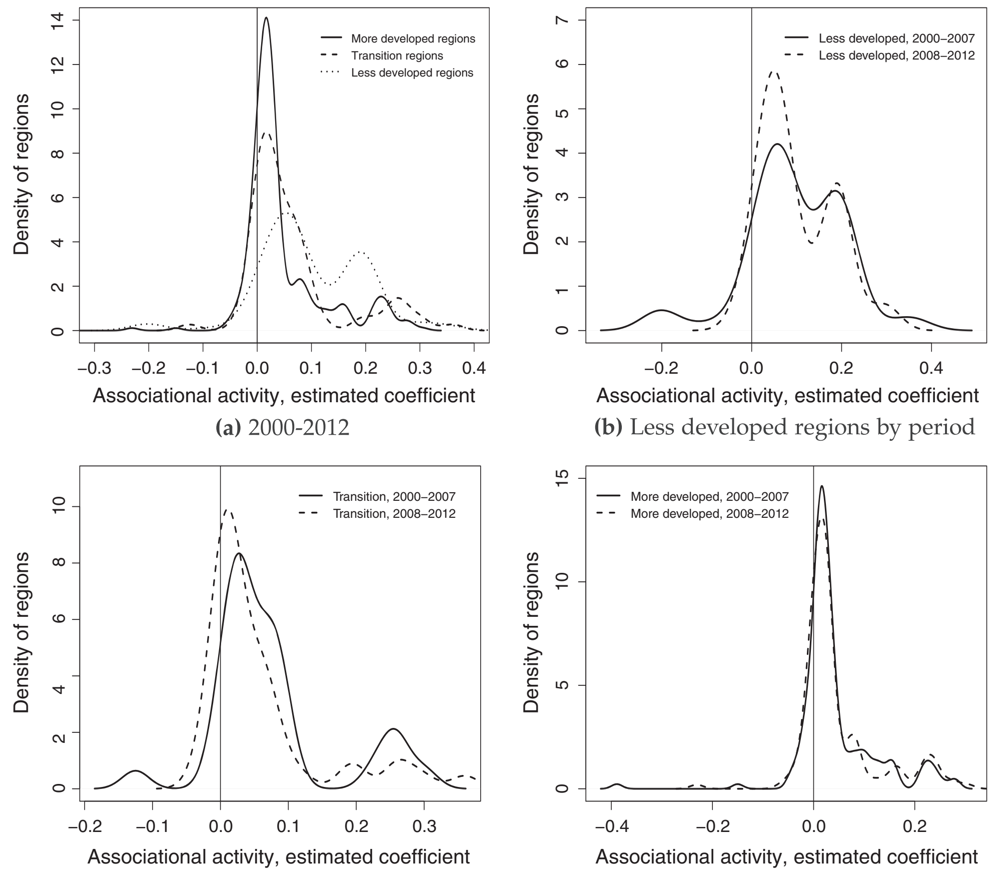
Notes: Estimates for a particular continuous regressor correspond to first (Q1), median (Q2) and third (Q3) quartile of the vector of partial effects for that regressor. Beyond each estimate the corresponding wild bootstrap standard error is in parenthesis. In all cases, estimations are performed considering that the rest of variables in the model remain constant at the median. Estimations include country fixed effects and time effects. In IV model 4, associational activity is instrumented by regional latitude, historical universities and the pronoun-drop characteristic in language. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively.

TABLE 7 Local linear least squares, median estimates for associational activity in Model 4 for different income groups

	Dependent variable: Patents (logs)		
	2000–2012	2000–2007	2008–2012
Full sample	0.031***	0.032***	0.028***
	(0.011)	(0.012)	(0.011)
Less developed regions	0.037***	0.076**	0.067***
	(0.013)	(0.004)	(0.022)
Transition regions	0.030***	0.045**	0.024***
	(0.009)	(0.020)	(0.009)
More developed regions	0.016**	0.022***	0.022***
	(0.008)	(0.009)	(0.008)

Notes: Values correspond to the median of the vector of partial effects for associational activity in each subgroup. Beyond each estimate wild bootstrap (399 repetitions) standard errors are provided in parenthesis. *, ** and *** denote significance at 10%, 5%, and 1% levels, respectively.

for the group of more developed regions, with a main mode on the right side but very close to zero. For regions in transition we distinguish two modes, which become more apparent for the group of less developed regions. Separate results by period are also provided. The between group differences found for the entire period hold for the two separate subperiods. However, the Li (1996) tests fail to reject within group disparities by period. Only for transition regions is the equality of distribution weakly rejected (10%).



(a) 2000-2012
(b) Less developed regions by period
(c) Transition regions by period
(d) More developed regions by period

FIGURE 4 Estimated coefficients for associational activity in model 4, regions in different income groups

5.3 | Mapping results by region

The above results are insightful, but still relatively general. Figures 5 and 6 are much more specific, mapping results by region. Regions shaded in grey correspond to nonsignificant effects. The results show an interesting pattern, persistent in the two periods. The effects of associational activity, which have a remarkable country level pattern, are particularly intense in the new EU members, especially in Poland, Latvia and Estonia, together with some former EU 15 economies such as Sweden, Spain and the South of Finland, where the capital Helsinki is located. The largest effects are found for particular locations such as the South of Spain, and the region of Bulgaria's capital city Sofia, Yugozapaden. Significant effects ranging in the interval 0.00–0.10 are also found in the UK and the Irish regions, the South of Italy, Malta, Cyprus, Greece and Romania, together with the North of Germany and the Danish regions, although the latter only in the first period. However, in regions with relatively high levels of innovation (mostly regions in the core of Europe) the effects are non-significant. With the exception of the UK, Ireland, Sweden, and the South of Finland, these results give some support to the idea that associational activity plays a major role in the less developed regions.

The drivers of that heterogeneity might be manifold, as regions are very different in many aspects. Some insights can be derived from the innovation typologies identified by Camagni and Capello (2013), which match quite well with the findings. In particular, associational activity is especially relevant in imitative innovation areas (mostly regions from Eastern and Central Europe and the South of Italy), smart and creative diversification areas (Spain, Greece and the North of Poland) and in some specific smart technological application areas (Sweden, Ireland, the UK and Denmark).

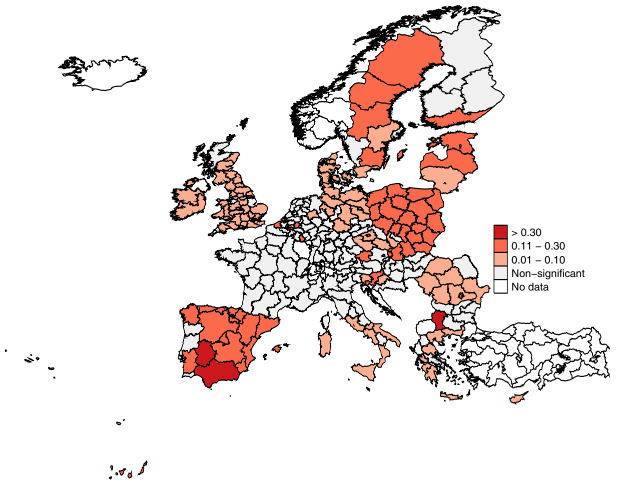


FIGURE 5 Estimated coefficients for associational activity, model 4 (2000–2007)

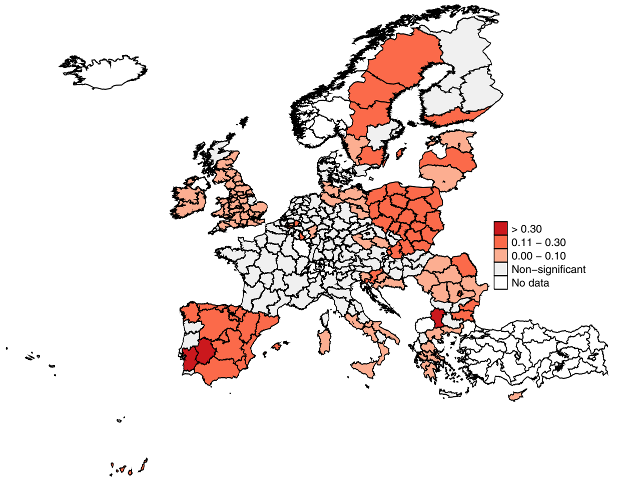


FIGURE 6 Estimated coefficients for associational activity, model 4 (2008–2012)

The former are characterized by low R&D investment but high ability to attract and adapt foreign knowledge. The two latter take place also in low R&D investment areas but they take the most of the embedded knowledge in the existent human capital. In these scenarios, the role of associations seems crucial for innovation. Nevertheless, in the core of Europe most regions are categorized as applied science areas and science-based areas. These typologies of innovation rely much more on R&D investment and in knowledge inputs coming from regions with a similar knowledge base, so individuals exchange alike information instead of non-redundant knowledge. In those cases, associations may play a more modest role.

Following Camagni and Capello (2013), cooperation is one of the policy prescriptions for regions where the results suggest a greater effect of associations. In particular, following the authors, it is important to favour creativity and the entrepreneurial spirit to promote social values, diversity and an innovation-friendly environment that reduce barriers to innovation. Therefore, the results would be aligned to their policy prescriptions, which find some support in the data.

The results might be also compatible with Isaksen and Trippl's (2017) arguments, based on the analysis of regional innovation systems (RIS). They argue that peripheral regions lack the necessary conditions to promote science-based industries and related high-tech industries. In those areas, companies rely more on cooperation with external actors and on the flows of informal knowledge embedded in the researcher's network. Combining RIS with innovation modes, the authors also suggest that the doing-using-interacting (DUI) mode, which dominates in traditional, cultural and creative industries is more based on informal learning, interactions and the know-how acquired by the experience. These structures also involve employees, develop team work, joint projects and problem-solving groups. In contrast, the science–technology–innovation (STI) mode is more common in research-intensive industries located in the core regions of Europe, and it depends more on formal and codified knowledge. In any case, although the heterogeneity found in the results generally finds some support in Camagni and Capello's (2013) and Isaksen and Trippl's (2017) patterns of innovation, the match is far from perfect and these ideas should be taken as potential explanations only.[19]

6 | CONCLUDING REMARKS

This paper has analysed the geography of social capital, in particular the associational dimension, and innovation in the European Union. It explored that link for the years 2000–2012, also considering shorter periods in order to distinguish between expansion years (2000–2007) and crisis years (2008–2012). In a preliminary approach, OLS estimations predict a positive average causal effect from associations to innovation, aligned with previous findings. The contribution of the paper, however, comes from the exploration of parameter heterogeneity in the associations–innovation link, both across regions and over time. This is possible by running non-parametric regressions, using the methods by Racine and Li (2004). The main conclusions are: (i) the effects are generally greater in less developed and transition regions, although there are exceptions such as some of the UK, Irish, Spanish, Danish and Swedish regions; (ii) they correspond mostly to peripheral regions of the EU; (iii) the results are virtually the same for the expansion and the crisis periods. This indicates that the positive payoff of associations does not suffer remarkable variations during unstable and turbulent periods such as the recent crisis, whose effects went beyond purely economic aspects to have notable social and political consequences in most of the EU countries.

In general terms, these results complement previous findings in the literature, which highlighted the importance of the 'social filter' (Crescenzi & Rodríguez-Pose, 2013), and other contributions finding a positive effect of different dimensions of social capital on innovation in the European context (Akçomak & Ter Weel, 2009; Akçomak & Müller-Zick, 2015; Barrutia & Echebarria, 2010; Hauser et al. 2007; Kaasa, 2009). If the EU Cohesion Policy is aimed at improving competitiveness and well-being in the less favoured regions, associational activity as a form of social capital should be considered as a powerful tool to achieve these objectives. This is, for example, the case of the current H2020 programme, which attaches importance to consortiums in awarding competitive projects. They incentivize association between agents from different countries and institutions, creating knowledge networks, so that we might argue that policy-makers are on track.

Nevertheless, the general results cannot be generalized for all regions. Our findings reveal a high degree of heterogeneity, and support also the need to design region-specific policies, as claimed by recent voices in the literature such as Barca (2009), Barca et al. (2012) or Camagni and Capello (2013). In particular, policies encouraging association would be particularly interesting for the less developed and transition regions from the periphery of the EU, and also for some regions in the UK, Ireland, Denmark and Sweden. These ideas might be combined with the innovation patterns and smart innovation policies in the EU defined by Camagni and Capello (2013) and Isaksen and Trippl (2017), described in the previous section. These policies aim to boost regional innovation capabilities enhancing the local expertise and focusing on specific interventions in each territory according to its particularities. In that sense, an important policy implication of this paper is that policies should also take into account the specific role of associational activity.

[19] Exploring the determinants of parameter heterogeneity in detail would deserve a specific research. This can be an interesting avenue for researchers in the near future.

Finally, the paper has some limitations that should be interpreted as opportunities for future research. First, social capital is a multifaceted concept, but this paper has considered only one dimension. Therefore, as argued by Bjørnskov (2006), Hauser et al. (2007) and Murphy et al. (2016), different results can be found for other dimensions. Second, the reasons why the causal relationship between associations and innovation is generally not significant for some core EU-regions deserve specific research. Although the level of regional development together with the categorization of innovation areas described in the previous section might be a potential explanation, other alternative arguments are: (i) the effect of associational activity might be particularly effective under specific policies and regulatory frameworks; (ii) associational activity might affect innovation through other mechanisms beyond those considered in Section 2. For example, complementarities between different forms of social capital, education and the degree of financial development have been found in the literature (see Bjørnskov, 2009; Guiso, Sapienza, & Zingales, 2004), but the underlying mechanisms are difficult to be disentangled. These are only some of the research initiatives on the academics agenda for the coming years that may clarify the complex geography of social capital and regional innovation in the highly heterogeneous enlarged EU.

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Resumen. Este artículo evalúa el papel de la dimensión de la actividad asociativa del capital social en la innovación regional para 257 regiones de la UE 28 en el período anterior a la crisis (2000–2007) y en el período de crisis (2008–2012). El análisis se lleva a cabo mediante el uso de regresiones no paramétricas tipo núcleo (*kernel*), que permiten examinar la heterogeneidad en el espacio y en el tiempo. Los resultados muestran que los efectos difieren ampliamente entre regiones, pero no se encontraron diferencias entre ambos períodos. En particular, los mayores efectos se observan en las regiones menos desarrolladas y en transición de la periferia. Por el contrario, para la mayoría de las regiones desarrolladas del núcleo de Europa el impacto no es significativo. Estos resultados podrían ser útiles para el diseño de políticas en el marco del programa Horizonte2020.

抄録:　本稿では、EU28カ国で257の地域における、世界金融危機以前(2000年~2007年)と危機の最中(2008年~2012年)の、地域イノベーションにおける社会資本の協会活動の側面の役割を評価する。空間上および時間上における異質性を探索することができる、フレキシブルなノンパラメトリックのカーネル回帰により分析を行った。結果から、地域全体で効果に大きな差があることが示されたものの、期間における差は認められなかった。注目すべきこととして、周辺部の後進地域 (less developed region)と移行地域 (transition region)に最も大きな効果が認められた。一方で、ヨーロッパの中核を成す先進地域 (developed region)のほとんどにおいて、有意な効果は認められなかった。この結果は、ホライズン2020のフレームワークにおける政策デザインに有用であると考えられる。