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Science and Technology Cooperation in Cross-border Regions: A Proximity Approach with Evidence for Northern Europe

Abstract: Given the sheer number of cross-border regions (CBRs) within the EU, their socio-economic importance has been recognized both by policy-makers and academics. Recently, the novel concept of cross-border regional innovation system has been introduced to guide the assessment of integration processes in CBRs. A central focus of this concept is set on analysing the impact of varying types of proximity (economic, cognitive, technological, etc.) on cross-border cooperation. Previous empirical applications of the concept have, however, relied on individual case studies and varying methodologies, thus complicating and constraining comparisons between different CBRs. Here a broader view is provided by comparing 28 Northern European CBRs. The empirical analysis utilizes economic, science and technology (S&T) statistics to construct proximity indicators and measures S&T integration in the context of cross-border cooperation. The findings from descriptive statistics and exploratory count data regressions show that technological and cognitive proximity measures are significantly related to S&T cooperation activities (cross-border co-publications and co-patents). Taken together, our empirical approach underlines the feasibility of utilizing the proximity approach for comparative analyses in CBR settings.

Keywords: science and technology cooperation; proximity; cross-border integration; cross-border regional innovation system; cross-border region; Northern Europe

Introduction

Due to the enlargement of the EU, the number of internal EU cross-border regions (CBR) has multiplied in the past twenty years. These CBRs have gained increasing amount of
political and scholarly attention. A specific interest of policy-makers has been to launch funding initiatives (through, for example, INTERREG programmes) in order to stimulate integration, economic development and joint innovations in the (usually) peripheral outskirts of nation states (European Commission, 2017). For academics, the CBRs have provided interesting ‘testing grounds’ for theoretical discussions and empirical accounts of, for example, the importance and impact of different types of proximity – nearness in space (geographical proximity) or relationships (relational proximity) – for cooperation, knowledge transfer, regional innovativeness and socio-economic integration (Makkonen & Williams, 2016; 2018). In these debates, geographical proximity per se is not considered as a key limitation for inter-regional cooperation across the border (since the regions are, in fact, adjacent to each other). However, (commonly) there are other types of dissimilarities between the adjacent sides of the border (simple examples being language, culture, legislation, etc.) that do impact the level of cross-border cooperation (negatively). In these settings national borders are seen not only as markers of administrative territorial boundaries, but also as barriers hampering the likelihood of inter-regional cooperation across borders. This is an issue that policy-makers and scholars are trying to overcome via cross-border funding mechanisms and academic research on these negative border effects on cross-border integration. This has led to the coining of a new innovation system concept, the ‘cross-border regional innovation system’ (CBRIS) (Lundquist & Trippl, 2013; Trippl, 2010).

Despite the evident importance of the topic, there are no existing empirical accounts which comprehensively validate the concept: earlier (case) studies commonly only look at a single CBR (rather than comparing CBRs or obtaining generalizable results for a large sample of CBRs) and only assess one dimension of cross-border integration,
Despite there being several – conceptually – identified and related dimensions (Makkonen & Rohde, 2016). This paper addresses this research gap by developing empirical measures for depicting cross-border proximity, utilizing a comparative statistical analysis of Northern European CBRs – specifically by applying publication, patent and sector-specific economic statistics – and by analysing the relationship between the various types of proximity and cross-border integration. The central research question is: are high levels of proximity linked to high levels of scientific and technological (S&T) cooperation in cross-border contexts?

Conceptual Framework

**Cross-border Regions as an Analytical Concept**

In colloquial language, CBRs refer to areas consisting of neighbouring territories belonging to different nation states. At first sight, therefore, the concept of CBRs seems to be a straightforward notion when applied in empirical settings. In practice, however, CBRs (both in the EU and globally) are very diverse in terms of their geographical coverage, socio-economic situation and cultural and institutional context (Perkmann, 2007a). Additionally, according to Blatter (2004, p. 530), cross-border cooperation has been transformed from the traditional geographically defined ‘spaces of place’ towards a more dynamic reality of ‘spaces of flows’, where CBRs are ‘functionally differentiated systems with variable and fuzzy geographic scales’ rather than clearly defined territorial units. Therefore, delineating CBRs for empirical research purposes is commonly done on an ad hoc basis depending on the intended scope of the analysis: administrative regions (Perkmann, 2007b), metropolitan areas (Sohn, Reitel, & Walther, 2009), and (twin-)cities (Anischenko & Sergunin, 2012; Sohn, 2017) are commonly used as the geographical
scale in empirical studies of cross-border integration and cooperation. Consequently, to provide a consensus view on the varying ways of delineating CBRs, Perkmann (2003, p. 157) has proposed that a CBR could be defined as ‘a bounded territorial unit composed of the territories of authorities participating in a cross-border cooperation initiative’.

**Cross-border Regions as a Practical Tool for Regional Development**

In addition to being an analytical concept in empirical research, CBRs also have practical connotations as being central elements in the EU’s integration and neighbourhood policies associated with regional development funding (Liikanen, 2008). While the conceptualization and implementation of, for example, the INTERREG cross-border initiatives is criticized by some (see e.g. Harguindéguy & Bray, 2009), this form of organized cross-border cooperation is also positively appraised. Specifically, it contributes significantly to improving physical cross-border connections, promoting economic and social cohesion in the EU, and bridging political-administrative gaps across borders (Medeiros, 2010; Oliveira, 2015). Thus, CBRs are central elements in current policy debates on regional innovation and development (European Commission, 2017; OECD, 2013).

**Cross-border Regional Innovation Systems**

Linking the rich literature on innovation systems to the idea that the long-term competitive performance of CBRs largely depends on their ability to intensify their integration and cooperation activities, the concept of CBRIS was first introduced by Trippl (2010). Understanding the obstacles to and enablers of cross-border knowledge transfer and innovation cooperation is highly relevant for facilitating the CBRs’ potential
for innovation (Trippl, 2010). As such innovation can be considered both to foster cooperation (Engel & del Palacio, 2009) and to be the outcome of such cooperation (Lucas, Rego, Vieira, & Vieira, 2017). Furthermore, the “innovation system approach” is designed for achieving a better understanding of the processes of knowledge production and transfer for improved regional competitiveness and development (Albert & Laberge, 2007). It can provide a promising tool for studying and facilitating joint innovation activities in CBRs. However, as noted by Trippl (2010), despite its obvious potential (Lundvall, 2007) and a few early explorations (Coenen, Moodysson, & Asheim, 2004; Koschatzky, 2000), the innovation system approach has not been fully applied in the context of CBRs (see also Makkonen & Rohde, 2016; Makkonen, Weidenfeld, & Williams, 2017).

In essence, similar to a regional innovation system (Autio, 1998; Cooke, 2002), a CBRIS is constituted from knowledge generation and diffusion (the public sector: research institutes, universities, intermediaries, etc.), and knowledge application and exploitation (the private sector: firms) subsystems. The main difference to a standard regional innovation system embedded in a single national context is that actors in CBRIS settings are operating within two or more national settings with varying legislation, language, cultural values and business practices. The ideal case of a CBRIS, that would significantly heighten the innovative capacity of a given CBR, would be a system characterized by intensive interactions and circulation of knowledge, resources and human capital within and between the two subsystems and across the border (Lundquist & Trippl, 2013; Trippl, 2010).
At the heart of the CBRIS concept lies the notion of knowledge transfer and international human mobility, together with the potential obstacles to diffusion and exchange of expertise and skills imposed by political, economic, institutional and cultural borders. In particular, the conceptual literature on CBRISs focuses on the importance of facilitating cross-border integration in order to enhance and sustain regional competitiveness and prosperity via promoting common regional identity, stimulating cross-border knowledge interaction, utilizing bridging organizations in brokering innovation contacts, facilitating dialogue and consensus and building cross-border policy networks and negotiation systems (Trippl, 2010). As such, CBRIS was developed as an analytical concept and a development tool. Firstly, it is a framework for analysing regional cross-border integration and cooperation. Secondly, studying integration in CBRs can also be a tool for policy-makers to foster development in border regions, since the different cross-border integration stages (see below) call for different policy approaches to foster cross-border cooperation and innovation. Initially simple measures, such as improving cross-border accessibility with infrastructure projects, might be sufficient in boosting cooperation and integration across the border, but as the level of integration increases the required (innovation) policy portfolio becomes more complex (Makkonen & Rohde, 2016; Trippl, 2010). Still, the concept of CBRIS has yet to receive substantial academic attention and, thus, its policy suggestions are based on a thin evidence base (Makkonen & Rohde, 2016). The few existing empirical studies of European CBRs concentrate their attention on case studies of individual (or very few) CBRs (Hansen, 2013; Kiryushin, Mulloth, & Iakovleva, 2013; Makkonen, 2015; 2016; Makkonen & Weidenfeld, 2016; Makkonen, Williams, Weidenfeld, & Kaisto, 2018; Muller et al., 2017; Peck & Mulvey, 2018; van den Broek & Smulders, 2014; 2015; van den Broek, Benneworth, & Rutten, 2018).
Types of Proximity, Integration and Cross-border Regional Innovation Systems

Lundquist and Trippl (2013) expand Trippl’s (2010) original CBRIS model by presenting a general framework for observing the levels of integration in CBRs. They seek to identify (conceptually) the different stages in the development of a potential CBRIS by dividing them into weakly–semi–strongly integrated innovation systems. This integration process occurs simultaneously in several dimensions along economic structures (innovative firms and clusters), science bases (regional knowledge infrastructure), technological linkages (cross-border knowledge/innovation interactions), the institutional set-up (cultural, social and institutional forms of cooperation), policy structures (innovation policies and public governance) and accessibility (time costs of crossing the border). Accordingly, weakly integrated systems experience little S&T cooperation due to large differences in economic structures and knowledge bases on the opposing sides of the border, institutional thinness and the existing strong ties between local firms and their domestic partners. Semi-integrated systems do have S&T cooperation, but it occurs in only a few industries. In contrast, strongly integrated systems are characterized by high levels of firm and academic cross-border S&T cooperation, significant cross-border knowledge flows and high levels of human mobility.

Since it is likely that there are only a few CBRs that have sufficiently strong interactions in all of the above-mentioned dimensions to be labelled as strongly integrated systems, Lundquist and Trippl (2013) label this ‘final’ stage as the most advanced form of cross-border integration, which most regions can only aspire to at present. However, depicting cross-border integration in a linear (or sequential) manner does not take into account
possible changes in bordering processes, where at times the effects of a border can be reduced (de-bordering) or reinforced (re-bordering). These temporal changes necessarily alter the dynamics of cross-border integration (Durand & Perrin, 2017).

This discussion of cross-border integration is closely tied to the literature on the role of distance and proximity in socio-economic interaction (Moodysson & Jonsson, 2007). As stated by Lundquist and Trippl (2013, p. 454), ‘cross-border areas where physical, functional and relational proximity coincide might become major places of new knowledge generation’. Recent literature on spatial scientometrics and inter-regional knowledge spillovers (see e.g. Cassi, Morrison, & Rabellotti, 2015; Frenken, Hardeman, & Hoekman, 2009; Greunz, 2005; Makkonen, 2015; Scherngell & Hu, 2011; Sun & Grimes, 2017) generally supports the importance of proximity in ‘easing’ inter-regional cooperation. This link between CBRIS and the proximity literature has acted as a catalyst for Makkonen et al. (2017) to propose an analytical framework for measuring cross-border integration by utilizing the concept of CBRIS. The framework is structured according to the various dimensions of integration as suggested by Lundquist and Trippl (2013), which all relate to different mixes of distinct types of relational (including cognitive and technological) proximity.

First, the dimension of economic structures is connected to the similarity of sectoral specialization patterns (related to technological proximity) and is operationalized by calculating sectoral employment shares for a set of industries in the respective sub-regions of a CBR. Second, the dimension of science bases’ is about cognitive proximity (similarity of knowledge bases), operationalized through the similarity of the scientific
fields of academic journal publications. Third, the dimension of technological linkages (related to both cognitive and technological proximity) is operationalized through the similarity of research and innovation activities measured by means of patent classes. Fourth, the dimensions of institutional set-up and policy structures is linked to institutional and social proximity (trust, similarity of informal constraints and formal rules shared by actors) across the sub-regions of a CBR. While difficult to operationalize, these latter dimensions could potentially be accounted for by dummy variables indicating the existence of shared policy goals, common institutions and practices aimed at enhancing integration across the border.

**Data Considerations**

*Delineating Northern European Cross-border Regions*

The empirical analysis conducted in this study pertain to a sample of the EU’s internal CBRs in Northern Europe (instead of the whole of the EU and its external borders). This constrains the time-consuming data collection process to a reasonable and manageable ‘pilot project’ while still including a sufficiently large number of ‘cases’ for comparative statistical analyses. Additionally, the sample selection recognizes the fact that the external borders of the EU, for example with the Russian Federation, still suffer from poor data availability at the regional level. Although the definition of Northern Europe is subject to debate, here it is considered to encompass the commonly included Nordic and Benelux Countries, the Baltic States, Ireland and the United Kingdom, together with the northern parts of Poland and Germany (Aalto, 2006; Neumann, 1994).
Although the question of where to draw the ‘borders’ of CBRs is necessarily subjective, there are some commonly applied examples of ways to delineate the CBRs of Northern Europe. The large statistical units of *Nomenclature d'Unités Territoriales Statistiques* (NUTS) NUTS-2 regions do not necessarily fit the delineations of functional or administrative CBRs (Perkmann, 1999). Therefore, these delineations are usually made on the basis of cultural ties, travel times, functional linkages or existing cross-border cooperation projects (Perkmann, 2003). Research on regional innovation and economic development repeatedly calls for the use of smaller regional units, since large statistical territories give distorted pictures of the levels of innovativeness of regions belonging to small or sparsely populated, including many Northern European, countries (Inkinen, 2005). For example, in the Baltic Countries there is only one NUTS-2 region. In a comparative sense, statistics on CBRs differ from the analysis of larger territorial units and country level data in providing a more detailed analysis of cooperation. Moreover, empirical studies show that in CBRs, international S&T cooperation is mainly linked to the global economic and scientific hubs (Hansen, 2013; Makkonen, 2015; Moodysson & Jonsson, 2007). This inevitably distorts the usability of crude averages of country-level statistics on S&T cooperation, mainly occurring between major research hubs, as metrics for depicting the situation in (peripheral) CBRs. This mismatch creates limitations in terms of the secondary data available for empirical studies on CBRs, which partly explains the scarcity of quantitative studies of cross-border integration, and their tendency to rely on limited sets of pre-existing descriptive data, such as cross-border traffic flows (Decoville, Durand, Sohn, & Walther, 2013; Matthiessen, 2005). As a point of departure, this study utilizes smaller regional units (counties or municipalities) when appropriate, and ‘manually’ assembles the data from various databases, in order to bring
new insights to the existing debate on regional cross-border integration and S&T cooperation.

Following the definition of CBRs by Perkmann (2003), the delineation of the CBRs is based on the descriptions provided by the Association of European Border Regions–AEBR (www.aebr.eu) and the Nordic Council of Ministers (NORDEN, 2004). In most cases, these definitions are applied as such. However, in some cases the existence of actual functional linkages between the furthest points of the delineated regions is questionable. In other words, they are geographically too large to be considered as CBRs (Perkmann, 1999). In these cases (particularly when the CBRs are divided by a sea), the CBRs are consistently defined to consist of (smaller) areas of roughly equal sizes in terms of population, and to include functional centres (cities) of similar scale on both sides of the border. The regions are presented in Figure 1.¹

![Figure 1 about here]

**Proximity Measures (Input) and Cross-border Science and Technology Cooperation (Output)**

We classify variables into input and output measures. While we basically assume that inputs and outputs are linked in a “cause→effect manner”, given the exploratory setup of our empirical analysis, we are careful not to overstate the causal nature of the identified empirical results. As outlined above, the selection of input variables follows the
functional logic of the proximity approach for regional innovation system analyses and includes the following measures (based on Makkonen et al., 2017):

1. **Economic Structures**: To measure similarity in economic structures across sub-regions in a CBR, we use data on sectoral employment shares calculated on the basis of Level 1 *Nomenclature statistique des Activités économiques dans la Communauté Européenne* (NACE) Rev. 2 classes. Sectoral employment shares are obtained from Eurostat and national statistics and are basically constructed as the number of employed persons per NACE category in relation to total regional employment. Averages for the years 2008–2012, depending on data availability per CBR, are used here.²

2. **Science Bases**: Data on science bases or cognitive proximity are based on counts of scientific articles according to their reported research fields for the different regional entities of the CBRs. These publication counts are collected from the Web of Science (WoS) database by applying Boolean command strings (to avoid double counting) based on the address fields of scientific articles, and are cumulated for the years 1991–2012. The starting year is selected to coincide with the re-establishment of independence in the Baltic States. The data are gathered according to the names of towns, municipalities and localities belonging to the studied regions.

3. **Technological Linkages**: Patent applications at the European Patent Office (EPO), including information on their main technology field measured through two-digit International Patent Classification (IPC) classes, are used as input data for this dimension. These data are gathered from the OECD RegPAT database and were cumulated for the years 1991–2012, by using a similar data collection
scheme as is utilized for the case of science bases, by removing duplicates by application number and IPC section. The RegPAT database reports patent data that is aggregated here to the regional level by utilizing the addresses of applicants. The database draws on underlying PATSTAT data and is documented in Maraut, Dernis, Webb, Spiezia, and Guellec (2008). For the purpose of this analysis, the January 2014 version of RegPAT is used.

The dimensions that mostly remain outside the realm of quantitative investigation, that is, institutional set-up and policy structures, or institutional and social proximity, are taken into account by using a dummy variable (named 'age'). This is done by assigning a value of one to CBRs in (old) established EU borders and a value of zero to those CBRs in areas which became internal EU borders only after the EU enlargement in 2004 (the Baltic Countries and Poland). The chosen dummy reflects the duration (history) of cross-border cooperation as a proxy for the strength of institutional governance in cross-border cooperation (Bergs, 2012; see also Medeiros, 2010).

The empirical operationalization of the different proximity measures is based on the methodology introduced by Jaffe (1986). For example, in the case of the variable science bases, the measure is calculated as follows (Equation 1):

\[
\text{Science bases}_{ij} = \frac{\sum_{r=t}^{n}(tf_{ir})(tf_{jr})}{\sqrt{\sum_{r=t}^{n}(tf_{ir})^2} \sqrt{\sum_{r=t}^{n}(tf_{jr})^2}}
\] (1)

where \(tf_r\) (‘term’ frequency) is the number of times a classification \(r\) (scientific field), arranged as vectors, is assigned to regions \(i\) and \(j\) which are both part of the same CBR. Thus, if two regions publish exactly the same proportion in each research area, the
measure would equal to one, or if they publish in totally dissimilar research areas, the measure would be equal to zero (McNamee, 2013; Peri, 2005). By converting into patent classes and sectoral employment share, the measure can be used to calculate similar values for economic structures and technological linkages, respectively.

The measure has some weaknesses since it does not differentiate between ‘close’ and ‘far’ classifications, but treats every classification as equally far (or close) from every other classification (McNamee, 2013). For example, even though intuitively the disciplines of geography and area studies share many common features, they are treated equally far from each other as, for example, geography and rheumatology. However, the measure and its close variants are widely applied as they offer a simple but consistent way to summarize the information inherent in tens of different classifications into a single metric (see e.g. Aldieri, 2013; Hoekman, Frenken, & Tijs, 2010; Joo & Lee, 2010).

Following the same logic as in the case of the input variables, data on cross-border co-publications and co-patents were collected from the WoS and RegPAT databases. In other words, the measures depict the numbers of patent applications at the EPO or published articles, in an individual CBR, that have applicants or authors from both sides of the border. These measures are normalized in terms of the population living in the region, that is, as co-patents and co-publications per one million inhabitants.
Of course, patents and scientific publications are surrogate measures for analysing regional innovativeness since, while commonly benefiting from good data availability, they suffer (as do all other proxy S&T indicators) from the disadvantage of not being confidently linked to actual innovations introduced into the markets (see e.g. Freeman & Soete, 2009; Hauser, Siller, Schatzer, Walde, & Tappeiner, 2018; Kleinknecht, van Montfort, & Brouwer, 2002). However, for the regional scale under study here, there really are no better alternatives for analysing all the municipalities and localities: there are no readily available innovation counts (literature-based innovation output indicator), survey (community innovation survey) or scoreboard (regional innovation scoreboard) data, which are commonly used as output measures for S&T and innovation. Additionally, patent applications and scientific publications are shown to work relatively well as proxy indicators for innovativeness (see e.g. Lim, 2004; Makkonen & van der Have, 2013; Nagaoka, Motohashi, & Goto, 2010). Furthermore, they act as complementary measures for each other by taking into account the knowledge generated in both the private and the public sectors: firms (the private sector) are likely to apply for patents to protect their novel findings, whereas publishing is the most important outlet of knowledge generation for academics working in public universities and public research institutes (Breschi, Lissoni, & Montobbio, 2005; Nelson, 2009). Thus, in the context of this paper, the use of patent and publication statistics, despite their limitations, provide useful proxies of knowledge creation, S&T and innovativeness.

Results

Descriptive statistics for the input and output measures are presented in Table 1. This shows that there are huge differences between the CBRs in terms of their proximity
measures and S&T cooperation activities. In terms of, for example, co-publications and co-patents there are several smaller CBRs, particularly those situated in the borders of the EU’s new member states, with no cross-border cooperation activity detectable from the WoS and RegPAT databases. In contrast, the Øresund region with its impressive 1401 cross-border publications, and the Dutch–German Maas–Rhein CBR with its remarkable 318 cross-border patents, per one million inhabitants, stand out as the top performing CBRs. This apparent non-normal distribution of the data renders the use of parametric analyses problematic and indicates the need to use non-parametric tests (here: Spearman’s rank-order correlation and the Mann-Whitney U test).

An initial pairwise correlation analysis of variables shows that the strongest correlation (both in terms of magnitude and statistical significance) can be observed for the link between proximity in science bases and co-publication activities (Table 2). We also obtain evidence for a statistically significant correlation between technological linkages and co-publications as well as between co-patents and all three proximity measures. However, we do not find a significant correlation between similarity in economic structures and co-publications indicating that not all proximity measures are equally important for different facets of S&T cooperation. In addition, the estimated pairwise correlations show that co-patent and co-publication activities are significantly positively related; further, population size is highly correlated with the number of co-publications in CBRs.
Non-parametric Mann-Whitney U test results further confirm the systematic link between proximity levels and S&T cooperation pointing to statistically significant differences between the above and below median performing CBRs when it comes to the proximity measures; significant variables with regard to both S&T outcome variables are shown in Figure 2. For CBR groups created on the basis of the median sample value of co-publications, the proximity in science bases is found to be significantly different across these two groups of CBRs ($p < 0.01$). For groups created on the basis of the median sample value of co-patents, the null hypothesis of the Mann-Whitney U test that distributional differences are insignificant across groups is rejected for proximity in economic structures ($p < 0.05$) and technological linkages ($p < 0.01$). As Figure 2 highlights, CBRs with high proximity in the associated dimensions perform better in the comparisons of actual cross-border S&T cooperation. Additionally, overall population levels ($p < 0.01$) are shown to link to the difference between above and below medium performance of CBRs in the category of co-publications. Finally, Mann-Whitney U tests also reveal that the age of the CBRs is statistically significantly related to differences in the intensity of cross-border co-publishing ($p < 0.05$) and co-patenting ($p < 0.01$): the more established intra-EU CBRs (within the EU-15) outperform the newly created (in 2004) intra-EU CBRs. This is as expected, since the figures for co-publications and co-patents in many CBRs involving new EU member states are zero (Table 1), apart from a few exceptions, most notably the Helsinki–Tallinn CBR.
To further account for the problem of spurious correlations stemming from an omitted variable bias in a bivariate estimation setup, we also run exploratory count data regressions to robustly identify significant linkages between proximity variables and S&T cooperation outcomes. As the results of negative binomial regressions in Table 3 show, the co-publication activity for the sample of CBRs is positively correlated with the proximity in science bases and further increases with population levels. Although we also find positive correlation between economic structures and the CBRs’ co-publication number, proximity in economic structures turns out to be statistically insignificant when applying a more rigorous estimation approach to account for the small-sample of our CBR data. With regard to co-patents, the results indicate that – besides population levels – technological linkages turn out to be positively related with the number of co-patents. Taken together, the explorative regression results support the empirical picture obtained from the nonparametric Mann-Whitney U tests for distributional differences between proximity measures when evaluated at different states of S&T cooperation. Cautiously stated, the empirical results provide the first indicative evidence for the significant role played by different proximity measures in affecting S&T cooperation activities in our sample of CBRs.

Conclusions and Directions for Further Research

The main aim of this paper is to develop and apply empirical measures for analysing the role of proximity for cross-border S&T cooperation and integration. Based on the
conceptual discussions of related empirical studies on CBRIS (see e.g. Lundquist & Trippl, 2013; Makkonen et al., 2017; Trippl, 2010), the identified relationship between the proximity in science bases (or cognitive proximity) and co-publications, as well as the relationship between economic structures, technological linkages and co-patents, underline our ex-ante expectations on the functioning of the proximity approach for investigating S&T cooperation in cross-border settings. That is, the identified relationships are in line with expectations. As stated by Trippl (2010) geographical proximity alone is insufficient to facilitate cross-border cooperation. Therefore, as shown here, adjacent sides of the border need to share some (basic) similarities in their knowledge bases, technological and economic structures in order for there to be a platform for integrating their innovation activities. While this finding has already contributed to analysing differences among CBRs within the Northern Europe and in internal EU borders, future studies should extend the empirical analyses in order to compare the role played by proximity factors in affecting S&T cooperation in other cross-border and inter-regional contexts.

Besides proximity, the empirical results also point to the role played by CBR size (measured through population levels) in S&T cooperation: the population base of CBRs needs to be large enough. This indicates that they must have a sufficient ‘critical mass’ of local research institutes and researchers to yield intensive cross-border S&T cooperation. Since several of the smaller regions, particularly the ones involving regions from the EU’s new member states, have either zero cross-border co-patent or co-publications, the descriptive statistics and tests indicate that the concept of CBRIS, and metrics for validating it, work better for samples including established border regions (within the EU-15) with a large population base. In other words, the proposed empirical measures
seem to work reasonably well in established urban CBRs, but quantitative measures of S&T cooperation may underestimate the de facto degree of cooperation in peripheral CBRs, particularly in less established CBRs (CBRs involving new EU member states).

Thus, to address the central research question of this paper, proximity in CBRIS dimensions is in general related to actual (and higher) cross-border S&T cooperation intensity, but not in all regions. Or, at least, this is not comprehensively detectable with quantitative S&T indicators. For these regions, other types of quantitative approaches, such as surveys (Makkonen & Williams, 2018) and social network analysis (González-Gómez & Gualda, 2017), should be additionally employed to explore the potential for CBRIS emergence. Furthermore, organizational and institutional cooperation could be investigated through desk studies of relevant policy documents of cross-border coalitions promoting integration in CBRs where these types of cooperation arrangements are in place (such as the Danish–Swedish Öresundskomiteen). Another example of exploring cross-border integration beyond S&T indicators includes the use of “attitude barometers” (Kaisto & Nartova, 2008). That is, surveys distributed to the populations of CBRs to scope the attitude and trust-based issues related to institutional and social proximity and cross-border cooperation.

Policy-makers in small and peripheral CBRs could also benefit from qualitative data analysis, since in these regions identifying subtle existing and potential forms of cross-border cooperation might be challenging with quantitative data such as S&T indicators. Regional stakeholders and funding bodies, such as the EU, need to tailor suitable tools to different types of CBRs for efficient facilitation of cross-border integration according to
varying characteristics such as their size and proximity in terms of their economic structures, knowledge bases and technological linkages. These aspects should be initially mapped or pre-assessed before selecting the most suitable policy measures. At the very least, policy-makers need to acknowledge that when it comes to innovation policies ‘one size does not fit all’ (Tödtling & Trippl, 2005): policies to encourage knowledge transfer and innovation in CBRs should diverge between the different development stages of cross-border integration (Trippl, 2010) and their size (in terms of population). The measures depicted in this paper can help to design these new policies and particularly assess the outcomes of existing ones. More specifically, EU policy-makers, for example, could benefit from the use the suggested methodology when setting up objectives for and evaluating the success of cross-border cooperation programmes aimed at facilitating knowledge transfer and innovation processes in CBRs.

Finally, this paper, as with most empirical studies on CBRIS, does suffer from data-related and methodological limitations. Firstly, the data presented on cross-border integration are commonly rather static. In order to discuss the levels of integration as an evolutionary (re- or de-)bordering process (Durand & Perrin, 2017), extensive time-series data are required for all the variables included in the analysis. Secondly, this paper relies on single – but well-established – measures for individual types of proximity and cross-border cooperation. Since the use of co-publication and co-patent data to measure knowledge flows and cooperation has shortcomings (as discussed in the ‘input’ and ‘output’ chapters above), the issue of whether there are other useful supplementary, or superior, indicators for measuring proximity in cross-border settings remains unresolved. For example, the use of EU framework and Erasmus student and university staff mobility programmes, cross-border commuters and cross-border trade patterns data, as
exemplified in Maggioni and Uberti (2009), Schernegg and Barber (2009), Makkonen and Weidenfeld (2016) and Cassi et al. (2015), could offer valuable additional insights for the evaluation of CBRIS.

Thirdly, the number of CBRs incorporated into the analysis here – although offering already a significant contribution and improvement compared to the single CBR case studies that characterize the CBRIS literature (Makkonen & Rohde, 2016) – still remains rather limited. Finally, the analysis does not take into account recent discussions on related variety – the co-existence of different but related industrial sectors and scientific fields (Frenken, van Oort, & Verburg, 2007). This could provide a more fruitful base for heightened cross-border innovativeness than high similarity: if the regions are too similar to each other, there is little to learn from the adjacent side of the border (Makkonen et al., 2017). While analysing related variety in cross-border contexts poses challenges for empirical settings (Makkonen & Rohde, 2016), one step forward would be to calculate a more accurate Mahalanobis proximity measure by analysing which scientific fields or IPC sections are frequently observed together within individual articles or patents and, thus, could be judged to be related to each other (Aldieri, 2013).

Clearly, data issues play a significant role in these caveats, since extensive secondary time-series data for the variables discussed here are largely unavailable, and/or since the data collection processes for this kind of information include several time-consuming steps. This is also likely to be the case with other potential measures of proximity and integration. Thus, it remains a task for further studies to repeat the analysis conducted here with alternative variables, different ways of measuring them, more cases (CBRs)
and (extensive) time-series data to further investigate in greater detail the relationships that have been identified in this paper. These more extensive data collection efforts would also allow for the use of more refined statistical and econometric methods. However, to conclude: as the very first substantial comparative empirical attempt to statistically validate the concept of CBRIS, this paper does provide novel insights into an increasingly significant set of economic relationships, and therefore offers a platform for further studies to build on.

Endnotes

1 Additionally, for methodological and data related reasons: 1) Maas–Rhein is treated as three pair-wise (Belgian–German, Belgian–Dutch and Dutch–German) CBRs, 2) in the case of Tornio River Valley, Livonia, Country of Lakes and Neman, the parts of the CBRs belonging to non-EU counties (Belorussia, Norway and Russia) are excluded and 3) in the case of Neiße–Nisa–Nysa and SaarLorLux, the Czech and French parts, respectively, of the CBRs are delineated to belong outside of ‘Northern Europe’.

2 The EU classification for NACE codes (NACE Rev. 2) was updated in 2008 (Eurostat, 2008), which imposes a break in the time-series data on regional employment figures in the EU between the contemporary data and the older data that has been compiled on the basis of earlier classification procedures.

3 Unfortunately, for patent applications (due to the RegPAT database utilized) we are restricted to using NUTS-3 categories, which in some cases do not fit the delineated CBRs. Thus, in some cases the results related to co-patents might overestimate the ‘real’ depth of cooperation. However, NUTS-3 categories are still a preferred solution in the case of CBRs instead of using the commonly applied, but significantly larger, NUTS-2 regions.

4 Due to the limitations inherent with using the inventor field in identifying cross-border patents, the information in the applicant field to account for ‘true’ collaborations is utilized (Bergek & Bruzelius, 2010). These figures are significantly lower than in the case of using inventor level data. However, the
inventor level data arguably gives more information concerning labour market mobility than actual cross-border S&T cooperation. For example, in the case of Øresund a significant number of Danes have moved to the Swedish side of the border due to housing market price differentials, but continue to work in and, thus, commute to Denmark (Makkonen, 2016).

For the regression analysis we do not transform the outcome variables into population-based intensities but include the latter variable as an additional regressor in the econometric model.

The estimated coefficients are transformed to incidence-rate ratios (IRRs) and both heteroscedasticity-robust and bootstrapped standard errors are calculated to address the problem that asymptotic inference in small samples can be unreliable (Efron, 1981).

References


*European Planning Studies, 13,* 449–473.


Figure 1. The delineated “cross-border regional innovation systems” of Northern Europe.

161x160mm (300 x 300 DPI)
Figure 2. Cross-border co-publishing and co-patenting intensity according to proximity measures.

107x60mm (300 x 300 DPI)
Table 1. Descriptive statistics of input and output variables.

<table>
<thead>
<tr>
<th>CBR Border</th>
<th>Population</th>
<th>Economic structures</th>
<th>Science bases</th>
<th>Technological Linkages</th>
<th>Co-publications per 1 million inhabitants</th>
<th>Co-patents per 1 million inhabitants</th>
</tr>
</thead>
<tbody>
<tr>
<td>Tornio River Valley</td>
<td>FIN-SWE 101</td>
<td>200</td>
<td>0.984</td>
<td>0.500</td>
<td>0.923</td>
<td>0</td>
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<tr>
<td>Kvarken</td>
<td>FIN-SWE 459</td>
<td>750</td>
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<td>0.638</td>
<td>0.669</td>
<td>60.9</td>
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<td>Skärgård</td>
<td>FIN-SWE 85</td>
<td>450</td>
<td>0.843</td>
<td>0.697</td>
<td>0.934</td>
<td>0</td>
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<tr>
<td>Helsinki-Tallinn</td>
<td>EST-FIN 1658</td>
<td>550</td>
<td>0.907</td>
<td>0.852</td>
<td>0.690</td>
<td>403.4</td>
</tr>
<tr>
<td>Øresund</td>
<td>DEN-SWE 2965</td>
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<td>0.963</td>
<td>0.953</td>
<td>0.747</td>
<td>1400.9</td>
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<tr>
<td>Spønderjylland-Schleswig</td>
<td>DEN-GER 670</td>
<td>300</td>
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<td>0.251</td>
<td>0.827</td>
<td>4.5</td>
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<td>Fehmarnbelt</td>
<td>DEN-SWE 302</td>
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<td>0.987</td>
<td>0.217</td>
<td>0.756</td>
<td>0</td>
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<tr>
<td>Livonia</td>
<td>EST-LAT 184</td>
<td>400</td>
<td>0.937</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bartuva</td>
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<td>0.141</td>
<td>0</td>
<td>0</td>
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<tr>
<td>Country of Lakes</td>
<td>LAT-LIT 369</td>
<td>350</td>
<td>0.976</td>
<td>0.142</td>
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<td>Neman</td>
<td>LIT-POL 747</td>
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<td>0.647</td>
<td>0.252</td>
<td>0.289</td>
<td>0</td>
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<td>Pomerania</td>
<td>GER-POL 2306</td>
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<td>0.927</td>
<td>0.715</td>
<td>0.89</td>
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<td>0.896</td>
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<td>0</td>
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<td>Spree-Neiße-Bober</td>
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<td>650</td>
<td>0.901</td>
<td>0.701</td>
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<td>Neiße-Nisa-Nysa</td>
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<td>Em Dollart</td>
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<td>0.81</td>
<td>2.6</td>
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<td>EUREGIO</td>
<td>GER-NED 285</td>
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<td>0.997</td>
<td>0.644</td>
<td>0.855</td>
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<td>Rhein-Waal</td>
<td>GER-NED 2381</td>
<td>172</td>
<td>0.995</td>
<td>0.605</td>
<td>0.835</td>
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<tr>
<td>Rhein-Maas-Nord</td>
<td>GER-NED 184</td>
<td>927</td>
<td>0.996</td>
<td>0.770</td>
<td>0.861</td>
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<td>0.296</td>
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<td>Maas-Rhein-3</td>
<td>BEL-NED 146</td>
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<td>0.990</td>
<td>0.484</td>
<td>0.635</td>
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<tr>
<td>Scheldemond</td>
<td>BEL-NED 1527</td>
<td>100</td>
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<td>0.740</td>
<td>0.968</td>
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<td>SaarLorLux</td>
<td>GER-LUX 1531</td>
<td>300</td>
<td>0.871</td>
<td>0.780</td>
<td>0.941</td>
<td>83.6</td>
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<tr>
<td>Ireland-Wales</td>
<td>IRE-UK 1946</td>
<td>350</td>
<td>0.962</td>
<td>0.716</td>
<td>0.969</td>
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<td>East Border</td>
<td>IRE-UK 894</td>
<td>450</td>
<td>0.978</td>
<td>0.401</td>
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<td>IRE-UK 659</td>
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<td>4.5</td>
</tr>
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<td>North-West Border</td>
<td>IRE-UK 387</td>
<td>450</td>
<td>0.734</td>
<td>0.501</td>
<td>0.707</td>
<td>7.7</td>
</tr>
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</table>

Average: 1 201 710 0.936 0.496 0.698 105.7 39.4
Median: 1 021 600 0.966 0.520 0.807 6.1 7.6
Max: 2 965 300 0.999 0.953 0.969 1401 318
Min: 85 450 0.647 0.0 0 0 0

Sources: 1 Eurostat; 2 National Statistical Authorities; 3 Web of Science; 4 RegPAT.

Table 2. Pairwise correlations between variables.

<table>
<thead>
<tr>
<th></th>
<th>Co-publications</th>
<th>Co-patents</th>
<th>Economic structures</th>
<th>Science bases</th>
<th>Technological linkages</th>
</tr>
</thead>
<tbody>
<tr>
<td>Co-patents</td>
<td>0.668***</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Economic structures</td>
<td>0.306</td>
<td>0.407**</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Science bases</td>
<td>0.562***</td>
<td>0.451**</td>
<td>-0.095</td>
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<tr>
<td>Technological linkages</td>
<td>0.391**</td>
<td>0.424**</td>
<td>0.267</td>
<td>0.403**</td>
<td></td>
</tr>
<tr>
<td>Population</td>
<td>0.635***</td>
<td>0.364*</td>
<td>0.293</td>
<td>0.723***</td>
<td>0.318*</td>
</tr>
</tbody>
</table>

Notes: *** p < 0.01 level; ** p < 0.05 level; * p < 0.10 level.
Table 3. Negative binomial regressions linking proximity measures and S&T cooperation.

<table>
<thead>
<tr>
<th></th>
<th>Co-publications</th>
<th></th>
<th>Co-patents</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>IRR</td>
<td>Robust SE</td>
<td>Bootstrapped SE</td>
</tr>
<tr>
<td>Economic structures</td>
<td>4.129</td>
<td>(1.227)***</td>
<td>(5.973)</td>
</tr>
<tr>
<td>Science bases</td>
<td>4.987</td>
<td>(2.011)***</td>
<td>(3.186)**</td>
</tr>
<tr>
<td>Technological linkages</td>
<td>2.605</td>
<td>(1.879)***</td>
<td>(2.464)</td>
</tr>
<tr>
<td>Population</td>
<td>1.305</td>
<td>(0.037)***</td>
<td>(0.077)***</td>
</tr>
</tbody>
</table>

Notes: *** p <0.01 level; ** p <0.05 level; * p <0.10 level. IRR = incidence-rate ratio; SE = Standard Errors. Bootstrapped standard errors have been calculated based on 200 replications. The variables Science bases, Linkages and Economic structures have been standardized (standard score) for estimation, while population has been log-transformed. For both estimated equations a test for over dispersion in the data favours the negative binomial specification over the nested Poisson specification.