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Abstract

Regional capabilities are regarded a pillar of Smart Specialization Strategy (S3). There is yet little focus in S3 policy on the role of inter-regional linkages. Our study on 292 NUTS2 regions in Europe finds that inter-regional linkages have a positive effect on the probability of regions to diversify, especially in peripheral regions. What matters is not being connected to other regions *per se* but being connected to regions that provide complementary capabilities. Finally, we propose a new indicator that enables regions to identify other regions as strategic partners in their S3 policy, depending on the presence of complementary capabilities in other regions.

Keywords: Smart Specialization, relatedness, inter-regional linkages, regional diversification, complementary capabilities

JEL codes: O25, O38, R11

1. Introduction

There is a large body of literature showing that regions build on existing capabilities to develop new activities (Boschma 2017; Hidalgo et al. 2018; Balland et al., 2019). Local capabilities as a source of regional change have been regarded as a pillar of Smart Specialization Strategy (S3) in the EU from its very start (Foray 2015; Radošević et al. 2018). The objective is building competitive advantage in new domains in which regions possess capabilities (Foray et al. 2009; McCann and Ortega-Argilés 2015). What attracted little attention is that S3 also required regions to identify potential links of their privileged domains with other regions in Europe. Despite these S3 guidelines, there is little focus on the role of inter-regional linkages in Smart Specialization policy (Thissen et al. 2013; Uyarra et al. 2014, 2018; Radošević and Ciampi Stankova 2015; Iacobucci and Guzzini 2016; Sörvik et al. 2016; Santoalha 2018; Varga et al. 2018; Barzotto et al. 2019).

Inter-regional linkages are considered to give regions access to external knowledge that can tackle or avoid the tendency of regions to get locked-in (Camagni 1991; Grabher 1993; Bathelt et al. 2004; Hassink 2005; Boschma and Iammarino 2009; Tavassoli and Carbonara 2014; Grillitsch and Nilsson 2015; Miguelez and Moreno 2018; Eriksson and Lengyel 2019; Ascani et al. 2020; Hesse and Fornahl 2020). However, there is little understanding of how inter-regional linkages may affect the development of new activities in regions, and if found important, to what extent inter-regional linkages can compensate for weak or missing capabilities in a region. Studies on regional diversification have primarily focused on regional capabilities but neglected the role of inter-regional linkages (Boschma 2017; Whittle et al. 2020). The same applies to the literature on new path development that paid little to no attention to inter-regional links (Trippel et al. 2018). This may be one of the reasons why inter-regional connectivity is poorly implemented in Smart Specialization policy in Europe. Scholars have also mentioned that a systematic, well-accepted and easy-to-apply method to identify relevant links between regions is still missing or weakly developed ((Iacobucci and Guzzini 2016).

This paper makes a first step to fill these gaps in the scientific as well as the S3 literature. The first objective is to investigate the impact of inter-regional ties on technological diversification in 292 NUTS-2 regions in Europe for the period 1992-2016, on top of the impact of regional capabilities. Following Boschma and Iammarino (2009), we expect linkages giving access to additional capabilities in other regions that are related to existing capabilities in a region will have a stronger impact on the ability to regions to diversify. We do indeed find strong evidence for that: what matters is not being connected to other regions *per se* but being connected to regions that provide complementary capabilities. Having complementary inter-regional linkages significantly increases the probability of regions in Europe to develop new technological specializations. We also examined whether inter-regional linkages are more important for diversification in peripheral regions, as these regions are often perceived to have weak capabilities (Grillitsch and Nilsson 2015; Rodríguez-Pose and Wilkie 2019). Our study shows that peripheral regions tend to diversify less, but their capacity to diversify increases significantly when connecting to regions with complementary capabilities. The second objective of the paper is to propose a new indicator that can identify for each region and for each technology to what extent other regions in Europe have complementary capabilities that

are missing in a region. This information can be used by regions to design an S3 strategy in which strategic partnerships are developed with other regions, given their capabilities.

The report is structured as follows. The first section gives a short literature review. Then, we describe the dataset and the variables used. We present the empirical findings on the effect of different types of inter-regional linkages on regional diversification in Europe. We also present an indicator that regions in their S3 policy can use to map complementary capabilities in other regions. The final section concludes.

2. Inter-regional linkages and regional diversification

To develop new economic activities and upgrade existing activities in regions is a principal objective of S3 policy. Balland et al. (2019) argue that the S3 policy should target economic activities with high growth potential that can build on existing capabilities in regions. The idea is that regions are more likely to develop activities related to existing local activities because these provide similar (but not identical) capabilities, such as knowledge, skills, and institutions. Consequently, new capabilities that are needed to develop new and upgrade existing activities are easier to acquire when close to local capabilities (D’Adda et al. 2019). By contrast, unrelated diversification requires a complete transformation of local capabilities, which is accompanied by high costs and a high risk of failure, and thus unlikely to happen.

This claim has found confirmation in empirical research in the last decade (Boschma 2017). The product space literature provided evidence that the emergence of new export products in countries are no random events but strongly embedded in capabilities at the national scale (Hidalgo et al. 2007). The economic geography literature found a similar tendency of regions to diversify into new activities related to existing capabilities (Neffke et al. 2011; Kogler et al. 2013; Muneeppeerakul et al. 2013; Rigby 2015). Despite different research layouts, empirical studies find that related diversification is the rule: local capabilities condition which new activities are more likely to develop in regions. This principle of relatedness seems to hold, no matter what types of activities (industries, technologies, occupations, or scientific fields) are considered, what relatedness measures (skill-relatedness, product-relatedness, technological relatedness, input-output-relatedness, etc.) are employed, or at what spatial scales (local, regional, national, global) studies are conducted (Hidalgo et al. 2018).

However, these studies primarily focus on regional (and national) capabilities. As a result, they draw little attention to inter-regional linkages that could also affect regional diversification (Boschma 2017; Whittle et al. 2020). Also, the path development literature pays little attention to the role of inter-regional linkages for new path creation (Trippel et al. 2018). This is remarkable, as scholars have claimed for long that extra-regional linkages are crucial for regional development and prevent regions to end up in a lock-in situation (e.g. Camagni 1991; Asheim and Isaksen 2002; Bathelt et al. 2004; Hassink 2005; Giuliani and Bell 2005, Vicente et al., 2011).

In regions, there are strong forces at work that make individuals, firms and networks prone to lock-in. Access to information is limited, and, above all, firms have limited capacity to absorb

external information (Simon 1957). To reduce this uncertainty, firms tend to search for new knowledge close by (Nelson and Winter 1982), that is, in their own cognitive domains, in their own networks, and in their own local surroundings. Access to distant knowledge is poor in general, the more so when knowledge is tacit (Gertler 2003). Therefore, knowledge diffusion is often geographically bounded (Jaffe et al. 1993; Balland and Rigby, 2017). The potential downside of this tendency is too much inward orientation. Knowledge exchange with the same local actors may lose value over time (Maskell and Malmberg 1999) and can lead to cognitive lock-in a region (Nooteboom 2000). This makes there is a tendency of regions to get locked in and become over-specialized (Grabher 1993; Boschma and Lambooy 1999).

This lock-in process may be avoided or overcome by linking to agents in other regions, to get access to external knowledge pools (Maskell and Malmberg 2007; Crespo et al. 2014). Bathelt et al. (2004) argued that cluster firms need to supplement local knowledge with external knowledge, and for that purpose build global pipelines. Network studies have shown that well-performing firms in clusters connect to bodies of knowledge residing outside clusters (e.g. Giuliani and Bell 2005). Scholars have also stressed the crucial role of gatekeepers that link local actors to knowledge outside their regions (Morrison 2008; Graf 2011; Morrison et al. 2013; Breschi and Lenzi 2015; Broekel and Mueller 2018). However, there is yet little understanding of the role of inter-regional knowledge sourcing during the emergent phase of clusters (Ter Wal and Boschma 2011; Henn 2013; Vicente 2018).

There is evidence that lagging regions, in particular, rely on non-local linkages when innovating, because their own capabilities and local networks tend to be weak (Fitjar and Rodríguez-Pose 2011; Vale and Carvalho 2013; Grillitsch and Nilsson 2015). De Noni et al. (2018) showed, for instance, that firms in lagging regions are more innovative when engaged in collaborative linkages with knowledge-intensive regions. Barzotto et al. (2019) find that the level of extra-regional collaboration is often higher in peripheral regions where it promotes innovation. This suggests that regions with weaker capabilities benefit more from non-local knowledge inputs.

Scholars also explore how inter-regional trade linkages may be connected to S3 policy (Radosevic and Ciampi Stankova 2015; Brennan and Rakhmatullin 2018). Thissen et al. (2013) examined trade linkages between regions and how they affect demand-led growth (growth of markets in region's export destinations) and structural growth (development of new export products) in regions. The global value chain literature (Gereffi et al. 2005) has shown how regions play different roles in global networks: some regions act as centers of corporate control and host high-end activities like R&D, while other regions function primarily as branch plant economies. This has resulted in a division of labor in which regions may be locked-in in certain activities at the global scale (Blazšek 2016). This makes relevant the question of whether regions have possibilities to upgrade their position in existing value chains and enter into new value chains (Los et al. 2017). This literature on trade linkages has been less explicit, however, on how inter-regional linkages contribute to new path development (Trippel et al. 2018).

Few studies have assessed the importance of extra-regional linkages for new path development. Bahar et al. (2014) and Boschma et al. (2017) found that regions are more likely to develop new export industries in which their neighbor regions are already specialized. Neighboring regions also tend to have more similar export structures when they are connected. Andersson et al

(2013) found that the entry of new high-quality export products in regions is positively affected by high-quality imports. Santoalha (2018) looked at the role of cooperation inside regions and across regions. He concluded that both forms of cooperation boost regional diversification in Europe. Whittle et al. (2020) found that inter-regional collaboration networks had a positive effect on regional (related) diversification in Europe, especially when external knowledge sourcing is done in a diverse set of regions. What these studies do not account for is the nature of inter-regional linkages in terms of relatedness that may affect regional diversification.

Indeed, what these studies tend to neglect is that regions require absorptive capacity to exploit and benefit from external knowledge (Boschma and Iammarino 2009; Miguelez and Moreno 2015). This makes that not all non-local knowledge is of immediate relevance and not all linkages to other regions matter for the capacity of a region to diversify (Boschma et al. 2009). Using trade data, Boschma and Iammarino (2009) found that regional growth is not simply affected by extra-regional linkages. Instead, they found a positive effect of extra-regional linkages when the proximity between the knowledge base of a region and the external knowledge flowing into a region is neither too small nor too large. Boschma et al. (2014) looked at the impact of relatedness between local knowledge and the inflow of non-local knowledge on new biotech activities in cities. Barzotto et al. (2019) applied a relatedness framework while examining the role of extra-regional linkages for technological development in EU regions. Miguelez and Moreno (2018) examined the effect of extra-regional linkages on the type of innovations in regions. They found that extra-regional knowledge linkages have a higher impact on innovation in a region when the similarity between external knowledge flows and local knowledge is higher. Extra-regional linkages promoted radical innovations when the extra-regional knowledge is related, rather than similar to the existing knowledge base in the region.

What all these studies did not look at, however, is the effect of extra-regional linkages on regional diversification. Moreover, the question is still open whether access to non-local capabilities is important for regional diversification when relevant capabilities are missing in a region (Whittle et al. 2020). Grillitsch and Nilsson (2015) claim that non-local linkages do not necessarily complement local knowledge spillovers and can even compensate for the lack of local knowledge spillovers in peripheral regions. De Noni et al. (2017) argued instead that local and non-local linkages *in tandem* are crucial for knowledge creation and productivity in regions.

In sum, few studies to date have estimated the effect of inter-regional linkages on regional diversification, and no study yet has examined the extent to which the nature of inter-regional linkages (in terms of relatedness) has had an impact on the diversification process in regions. To address this gap in the literature, we examine the relative importance of inter-regional linkages for regional diversification in Europe, controlling for local capabilities. We also propose a new measure of complementarity in inter-regional linkages that enables a region to identify capabilities in other regions that might help the region to diversify in new activities.

3. Data, variables, and method

This section explains what data we used, what variables have been constructed, and what method has been employed to analyze the impact of regional capabilities and inter-regional ties on technological diversification in 292 NUTS-2 regions in Europe for the period 1992-2016.

Following other papers on regional technological diversification (Boschma et al. 2015; Rigby 2015), we estimate an entry model that assesses the probability that a region specializes in a new technology. We use patent data that are derived from the OECD REGPAT dataset (2019 version). In the study, we assigned patents to 654 technological classes (4-digit CPC), and to 292 European regions (at the NUTS-2 level), based on the address of inventors. These include regions in all EU-28 countries and the four EFTA-countries (Iceland, Liechtenstein, Norway and Switzerland).

The dependent variable is the entry, or not, of a new specialization in a technology in a region. Following other studies (e.g. Rigby 2015; Balland et al. 2019), we calculate the Relative Technological Advantage (RTA) to assess whether a region becomes specialized in a technology that is new to the region. RTA is a binary variable that takes the value 1 when a region possesses a greater share of patents in technology class i than in the reference category (the EU as a whole), and assumes value 0 otherwise. In other words, a region r has a RTA in the production of technological knowledge i ($r = 1, \dots, n; i = 1, \dots, k$) such that $\mathbf{RTA}_{r,i}^t = \mathbf{1}$ if:

$$\frac{\text{patents}_{r,i}^t / \sum_i \text{patents}_{r,i}^t}{\sum_r \text{patents}_{r,i}^t / \sum_r \sum_i \text{patents}_{r,i}^t} > 1$$

As other studies on regional diversification (Boschma 2017), a linear probability model is estimated to assess the probability that a region develops RTA (i.e. $\text{RTA} > 1$) in a new technology. The entry probability of a new technology is assessed for time windows of 5 years. As we have patent data for the period 1992-2016, we calculate this entry probability for 5 subsequent periods (1992-1996; 1997-2001; 2002-2006; 2007-2011; 2012-2016).

All independent variables are measured in the period before the time window of 5 years. Our first main variable of interest is the role of relevant regional capabilities. As other studies (e.g. Hidalgo et al. 2007; Boschma et al. 2015; Rigby 2015), we construct a Relatedness Density (RD) measure to assess the effect of regional capabilities on technological diversification in European regions. RD is measured as the degree of proximity (relatedness) between a technology and the technological portfolio of a region. This requires two steps.

First, we calculate the degree of relatedness between each pair of technologies for a total of 654 CPC technology classes using co-occurrence analysis. This measures the frequency of occurrence of combinations of two technology classes on a patent document. We normalized these co-occurrences using the cosine similarity index. Second, this relatedness information is used to calculate the relatedness density (RD) measure. That is, for each region r , we calculated the density of technology production in the vicinity of individual technologies i . Following Hidalgo et al. (2007) and Boschma et al. (2015), the density of knowledge production around a given technology i in region r at time t is derived from the technological relatedness $\varphi_{i,j,t}$ of technology i to all other technologies j in which the region has a RTA, divided by the sum of

technological relatedness of technology i to all the other technologies j in the reference region (Europe as a whole) at time t . RD takes a minimum value of 0 when there are no technologies related to technology i present in region r at time t , while it takes a maximum value of 100 when all technologies related to i are present in region r at time t :

$$\text{RELATEDNESS_DENSITY}_{i,r,t} = \frac{\sum_{j \in r, j \neq i} \varphi_{ij}}{\sum_{j \neq i} \varphi_{ij}} * 100$$

The other main variable of interest is the role of inter-regional linkages. We developed two measures to capture the effect of inter-regional linkages on regional diversification. The first indicator is based on co-inventors residing in multiple regions, following other studies using patent data (van der Wouden 2018; Le Gallo and Plunket 2020; Whittle et al. 2020). It measures the number of linkages (NL) inventors in a region have with inventors in other NUTS2 regions.

The second indicator captures complementarities in inter-regional linkages. As discussed before, we expect that linkages that give access to additional capabilities in other regions that are related to existing local capabilities to have a stronger impact on regional diversification. We constructed a new variable called Complementary inter-regional Linkages (CL) that measures for each potential new technology i the extent to which a region r is linked with other regions s that are specialized in technologies j to which the new technology i is related, but that are missing in region r (that is, in which region r is not specialized). In other words, this variable aims to capture relevant capabilities that are missing in a region but that might enhance the probability of the region to diversify into a new technology when the region has access to these relevant capabilities through co-inventor linkages with other regions.

It takes six steps to construct this variable CL for a region r and a technology i . The first step is to measure the relatedness density (RD) around technology i in all regions s , as explained above. The second step is to determine for region r which technologies j are missing in region r ($\text{RTA} < 1$) to which technology i is related. The third step is to determine which regions s are specialized in these technologies j ($\text{RTA} > 1$) related to technology i that are missing in region r . The fourth step is to sum all RD scores around technology i for all regions s (as defined in the first step) that have a specialization in technologies j ($\text{RTA} > 1$) in which region r is not specialized (as defined in step 3). This is called RD added: it measures the amount of RD that can potentially be added by other regions to the RD of region r in that technology i because these regions are specialized in technologies j related to technology i that are missing in region r . The fifth step is to determine the number of co-inventor ties a region r has with each region s , and multiply it with the RD added of each region s . So the more ties with another region, the more relevant the complementary capabilities from that other region will be for region r . The sixth step is to sum the scores in step 5 for all regions s , so we get a total score of CL for region

r in technology i , based on the RD added multiplied by the number of inter-regional ties¹. The score of CL will be higher, the lower the RD in region r and the more it is connected to regions that can add high amounts of RD to region r . The score of CL will be 0 when region r has a maximum of RD in technology i (so no need to connect to other regions), and when it has no inter-regional ties with regions that could potentially add RD to region r .

We take a fictional example. Let's assume that technology i is related to two technologies m and n , and that there are three regions r , s and t . Region r has a RTA in technology m , region s has no RTA in both technologies m and n , and region t has a RTA in both m and n . Region s will add 0% RD to region r ($0/2$), while region t will add 50% RD to region r in technology i ($1/2$). Then, we use information on the links (co-patents) between regions to see if region r actually collaborates or not with regions that can add RD. If region r actively collaborates with other regions that have a high potential of complementarity, CL will go up. Let's assume region r has 10 ties with region s , and 5 ties with region t . Then, the CL (total) of region r around technology i will be $= 0*10 + 50*5 = 250$. So the CL variable sums all RD added by other regions multiplied by the number of ties with these regions.

So far, we defined the role of regional capabilities and inter-regional ties. We also include two control variables. Data are taken from EUROSTAT. First, we include GDP per capita to account for the level of economic development in a region. We expect the higher the GDP per capita, the higher the probability of a region to diversify. Second, we take the level of population (log) to account for different population sizes of regions. Again, we expect a positive effect. Third, we included time-fixed effects. Appendix 1 provides summary statistics for all variables.

4. Main findings: inter-regional ties and technological diversification in regions

Figure 1 presents the findings of the regional entry model. What can first be noticed in Model 1 is that the coefficients of our control variables are positive and in most cases significant: population size and GDP per capita tend to increase the entry probability of new technologies in regions. Moreover, as expected, we find a positive effect of relatedness density (RD) in all specifications. This is a confirmation of earlier studies on the importance of relatedness for technological diversification of regions (Kogler et al. 2013; Rigby 2015; Balland et al. 2019).

Figure 1. Diversification model

	(1)	(2)	(3)	(4)
Relatedness Density (RD)	0.003*** (0.00003)	0.003*** (0.00003)	0.004*** (0.00004)	0.002*** (0.0001)
Number of inter-regional linkages (NL)		0.005*** (0.0003)	-0.025*** (0.001)	-0.017*** (0.001)

¹ An option is to divide this by the total number of inter-regional ties region r has, so we derive a CL score that takes the average of the RD added per inter-regional tie. We have used this alternative CL variable in the estimations, and the findings remain the same.

Complementarity inter-regional linkages (CL)			0.027***	0.018***
			(0.001)	(0.001)
RD*CL (interaction term)				0.0002***
				(0.00001)
GDP per capita	0.001***	0.0001	0.0002**	0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population (log)	0.015***	0.010***	0.011***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Period	-0.007***	-0.008***	-0.008***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.142***	-0.083***	-0.172***	-0.120***
	(0.010)	(0.011)	(0.011)	(0.011)
Observations	379,876	379,876	379,876	379,876
R ²	0.037	0.038	0.044	0.044
Adjusted R ²	0.037	0.038	0.044	0.044
Residual Std. Error	0.318	0.318	0.317	0.317
	(df = 379871)	(df = 379870)	(df = 379869)	(df = 379868)
F Statistic	3,658.418*** (df = 4; 379871)	2,970.927*** (df = 5; 379870)	2,885.502*** (df = 6; 379869)	2,522.347*** (df = 7; 379868)

Note:

* ** *** p < 0.01

How about inter-regional linkages, once we control for this effect of regional capabilities? In Model 2, we find a positive impact of the number of inter-regional connections (NL). Being connected to other regions shows a positive relationship with technological diversification. So, our findings suggest that both regional capabilities and inter-regional linkages tend to contribute to the entry of new technologies in European regions.

In Model 3, we add our new variable of complementarity in inter-regional linkages (CL). As expected, we found a strong and positive relationship: a new technology has a higher probability to enter a region when this region has connections with other regions that provide complementary (and thus relevant) capabilities concerning this new technology. What is also interesting to observe is that the positive effect of inter-regional connections *per se* (NL) turns into a negative effect, once we control for complementarity in inter-regional linkages (CL). This might suggest that inter-regional connections are costly: adding connections with other regions that are not relevant to the technological structure of regions comes with a price. So, our findings tend to suggest that it matters to whom you connect (in terms of access to complementary capabilities), instead of being connected *per se*. In Model 4, we have added an interaction variable between local relatedness and complementary inter-regional ties (RD*CL), to test whether the two are substitutes or complements. A negative relationship might suggest that weak capabilities in a region (as reflected by a low RD) could be compensated by strong inter-regional linkages. Our findings show that the interaction effect is positive and significant: the higher the internal relatedness in a region is, the stronger the possible impact of external relatedness. So, complementary inter-regional linkages tend to reinforce, not weaken, the effect of regional capabilities on technological diversification in regions in Europe.

This finding requires further exploration of the possible role of weak capabilities in regions in combination with inter-regional linkages. We take the example of peripheral regions, as scholars (e.g. Fitjar and Rodríguez-Pose 2011; Grillitsch and Nilsson 2015) have suggested that access to non-local capabilities is especially important for innovation in peripheral regions where strong and relevant capabilities are often found missing. We estimated the same diversification model as in Figure 1 but added several variables for peripheral regions. For the sake of simplicity, we define peripheral regions as regions that include all ‘less developed’ regions (regions with a GDP per capita lower than 75% of the EU average) and ‘transition’ regions (GDP per capita between 75 and 90%), following the criteria of EU Cohesion Policy. In the estimations reported in Figure 2, we include the peripheral regions as a dummy variable.

Figure 2. Diversification model – specification for peripheral regions

	(1)	(2)	(3)	(4)
Related density (RD)	0.003 ^{***} (0.00004)	0.003 ^{***} (0.00003)	0.004 ^{***} (0.00004)	0.002 ^{***} (0.0001)
Number of inter-regional linkages (NL)		0.001* (0.0005)	-0.025 ^{***} (0.001)	-0.016 ^{***} (0.001)
Complementarity of inter-regional linkages (CL)			0.026 ^{***} (0.001)	0.014 ^{***} (0.001)
RD*CL				0.0002 ^{***} (0.00001)
Peripheral	-0.006 ^{***} (0.002)	-0.049 ^{***} (0.004)	-0.014 ^{***} (0.005)	-0.049 ^{***} (0.005)
GDP per capita	0.723 ^{***} (0.091)	0.104 (0.102)	0.023 (0.102)	0.037 (0.102)
Population (log)	0.015 ^{***} (0.001)	0.013 ^{***} (0.001)	0.012 ^{***} (0.001)	0.012 ^{***} (0.001)
Period	-0.007 ^{***} (0.001)	-0.008 ^{***} (0.001)	-0.008 ^{***} (0.001)	-0.008 ^{***} (0.001)
RD*peripheral	0.0001 (0.0001)			
NL*peripheral		0.006 ^{***} (0.001)		
CL*peripheral			0.001 ^{**} (0.0005)	0.005 ^{***} (0.0005)
Constant	-0.136 ^{***} (0.010)	-0.091 ^{***} (0.011)	-0.169 ^{***} (0.011)	-0.107 ^{***} (0.011)
Observations	378,463	378,463	378,463	378,463
R ²	0.037	0.038	0.044	0.045
Adjusted R ²	0.037	0.038	0.044	0.045
Residual Std. Error	0.318 (df = 378456)	0.318 (df = 378455)	0.317 (df = 378454)	0.317 (df = 378453)
F Statistic	2,430.469 ^{***} (df = 6; 378456)	2,134.865 ^{***} (df = 7; 378455)	2,156.579 ^{***} (df = 8; 378454)	1,964.191 ^{***} (df = 9; 378453)

Note:

* ** *** p < 0.01

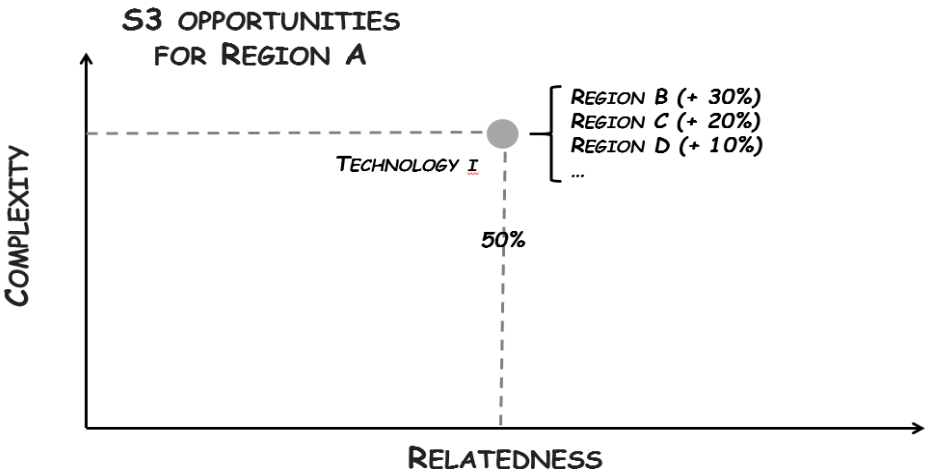
Figure 2 shows that peripheral regions tend to diversify less in new technologies. Then, we constructed variables interacting with Peripheral. We do not find evidence that the possible effect of regional capabilities (RD) is stronger or weaker in peripheral regions: the coefficient of the interaction term RD*peripheral is positive but not significant. However, as expected, model 2 shows the possible effect of inter-regional linkages on diversification is stronger in peripheral regions. This is in line with literature stressing that peripheral regions tend to rely more on inter-regional linkages because their own capabilities might be weaker. Model specifications 3 and 4 in Figure 2 shows there is also a positive and significant relationship with complementary inter-regional linkages in peripheral regions. This is interesting, as it suggests that while peripheral regions tend to diversify less in general, once they connect to regions that provide capabilities complementary to existing capabilities in peripheral regions, it will increase the probability of peripheral regions to diversify in new technologies.

5. Inter-regional linkages in a S3 framework

The question is how to incorporate this role of (complementary) inter-regional linkages in an S3 framework (Iacobucci and Guzzini 2016). One way of doing that is to identify regions that face similar technological challenges and opportunities. Regions that would look more similar should then connect to exploit economies of scale and to learn from each other. One could calculate a technological similarity measure to identify regions with a similar technological structure: this measures how many technologies two regions have in common (e.g. Autant-Bernard 2001; Moreno et al. 2005). However, similarity does not necessarily indicate complementarity. What we need instead is a complementarity measure that is technology-specific, so it can assess for each technology that a region wants to prioritize in its S3 which other regions can provide complementary capabilities. This measure can be used by European regions to identify regional strategic partnerships, given the capabilities in other regions.

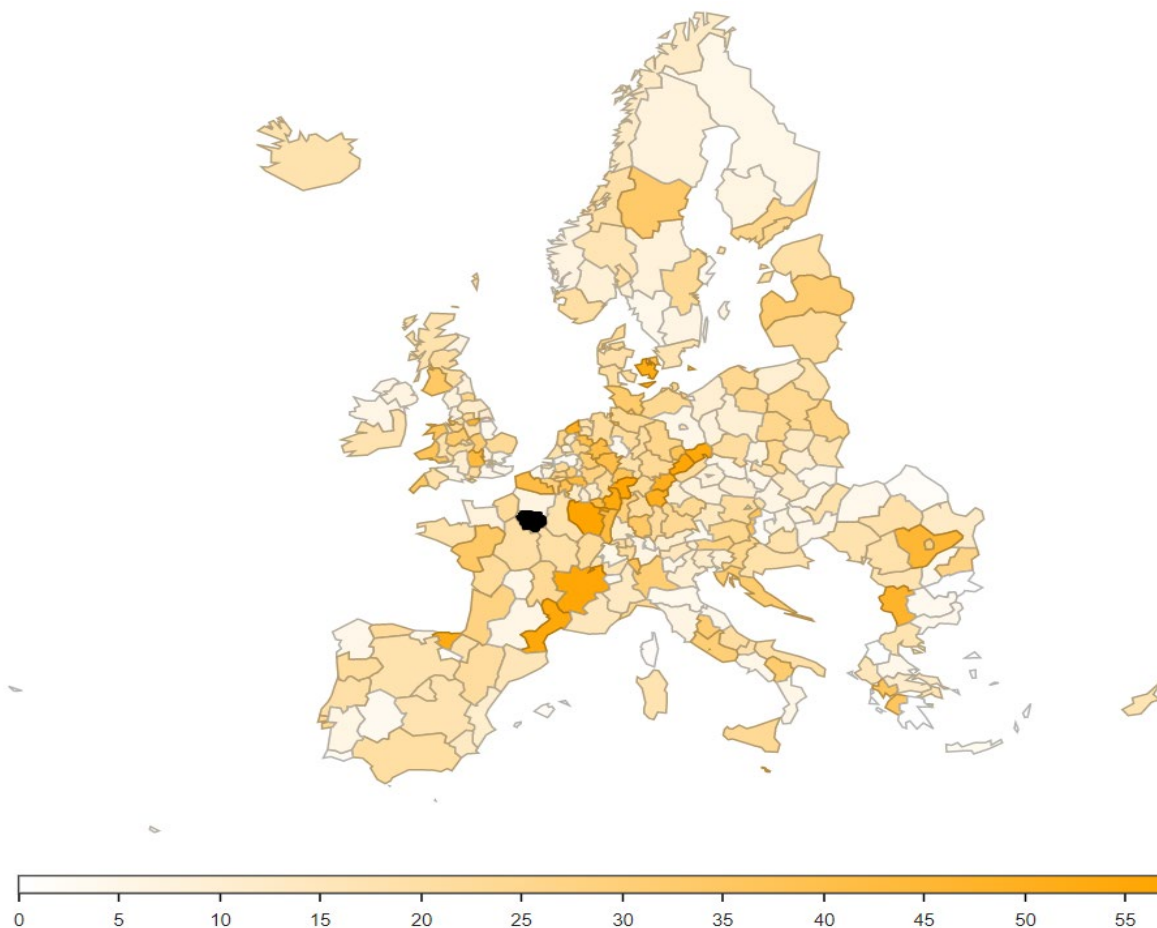
This complementary indicator maps for each region to what extent other regions in Europe have complementary capabilities that are missing in the respective region. This is illustrated further in Figure 3. The S3 of region A has the objective to develop a new technology *i* (like biotech) that is highly complex. Let's assume biotech is related to 10 other technologies, and region A has strong expertise in 5 out of these 10 technologies, leading to a level of relatedness density of 50%. Analyzing the technological portfolio of other European regions would reveal that region B has strong expertise in 3 technologies related to biotech in which region A has no expertise in. So, region A could develop a strategy in which it connects to region B. Through the creation of this inter-regional link, the relatedness density of region A would go up by 30%. So, it would make sense for region A to connect to region B in its S3, as it would significantly increase its probability to diversify successfully into a new biotech activity.

Figure 3. Diversification opportunities of a region through complementary inter-regional ties



Let’s take another example but this time based on real data. We show in Figure 4 to which European regions the Île-de-France region (marked black) could connect if it aims to develop new technologies in hydrogen as part of its S3. This requires identification of those technologies that can be considered related to hydrogen technology, followed by an identification of regions in which these technologies related to hydrogen are concentrated in Europe. Figure 4 shows the potential increase of the relatedness density in the Île-de-France region concerning hydrogen technology if it would connect to other European regions. It shows that European regions like the French Lorraine region, the Brussels region and the German region of Dresden could be interesting strategic partners for Île-de-France to develop new hydrogen technologies, as these regions possess large amounts of complementary capabilities that are missing in Île-de-France. Then it is for Île-de-France to find out if it is already connected to these regions and how that works in practice. If any deficiencies in these inter-regional linkages exist and Île-de-France region could something about it, the region could consider making it part of its S3.

Figure 4. Map of European regions with complementary capabilities for Île-de-France region in new hydrogen technologies



This complementarity measure enables regions to develop an S3 in which inter-regional linkages are incorporated. This measure helps to assess diversification opportunities of regions by identifying complementarities in capabilities across European regions. It aims to identify other regions that could act as strategic partners to develop new and more complex activities in a region as part of its S3. With this measure, it is possible to map for each technology (645 technologies) in each European region (292 NUTS-regions) to what extent other regions in Europe have complementary capabilities that are missing in a region. This information is useful for regions to identify and select other regions as the most relevant strategic partners because of complementarities in their capabilities. This sheds new light on the need to make connections between regions in Smart Specialization policy: it makes that the policy focus shifts from making inter-regional connections *per se*, to the exploitation of complementarities in other regions through the establishment of inter-regional linkages that give access to those.

6. Conclusion

Regional capabilities are regarded as a key pillar of Smart Specialization policy in the European Union, as they supply (related) internal capabilities in which a region can tap in to diversify into new activities and upgrade existing activities. However, there is yet little focus in S3 on the role of inter-regional linkages, and how to incorporate that in policy. A plausible reason is that there still is little understanding of how inter-regional linkages may give access to relevant

capabilities in which a region can tap into to diversify, how they might affect the development of new activities in regions, and to what extent these inter-regional linkages may compensate for a lack of relevant capabilities in regions. To fill this gap in the scientific and S3 policy literature, this paper attempted to estimate the possible effects of regional capabilities and inter-regional linkages on the ability of European regions to diversify into new technologies. We developed a new indicator of complementary inter-regional linkages that accounts for the fact that regions require absorptive capacity to exploit and benefit from the inflow of external knowledge through inter-regional linkages. This indicator aims to capture the impact of co-inventor linkages with other regions that provide access to relevant capabilities that are missing in a region, and that could increase its ability to diversify into a new technology.

The main findings can be summarized as follows. First, we find a positive relationship between inter-regional linkages and the probability of regions to diversify, on top of regional capabilities. This is especially true for inter-regional linkages that give access to capabilities not present in the region but related to existing capabilities in the region. In other words, a new technology has a higher probability to enter a region when this region has connections with other regions that provide complementary capabilities for this new technology. Second, the study has shown that it matters to whom a region connects in terms of access to complementary capabilities, while just being connected to regions does not seem to matter. This is in line with the philosophy of S3 policy that focuses on relevant capabilities, but also extends it to the targeting of inter-regional linkages that provide access to complementary capabilities. Third, we find that these complementary inter-regional linkages tend to strengthen, not weaken the effect of regional capabilities on the ability of regions to enter new technologies. This seems to imply that having no capabilities whatsoever, or having very weak capabilities in a region, cannot be compensated for by connecting to other regions, even when inter-regional linkages would give a region access to relevant (i.e. complementary) capabilities. Fourth, our analysis shows that peripheral regions tend to diversify less in new technologies. However, once peripheral regions connect to regions that provide capabilities that are complementary to their own capabilities, we found this increased the capacity of peripheral regions to develop new technologies. Finally, we constructed an indicator that can map for each region and for each possible technology the extent to which other regions in Europe have complementary capabilities that are missing in a region. This information is useful for a region because it gives an additional rationale to select and connect to specific regions as part of its S3, given the availability of complementary capabilities in other regions. Doing so, the policy focus of Smart Specialization shifts from making inter-regional connections *per se*, to the exploitation of complementarities available in other regions through inter-regional linkages.

Needless to say that this paper also has some limitations.

First, there are the usual caveats of using patent data to estimate diversification potentials in regions. This applies especially to peripheral or less urbanized regions where other types of capabilities in low and medium-tech may be more important for diversification. This requires additional analyses using data on industries or occupations that have proven to be useful to identify diversification potentials in peripheral regions (Balland and Boschma 2019). These data can be used to conduct a similar analysis on the role of inter-regional linkages for regional diversification, using trade data (Boschma and Iammarino 2009) or labour flow data (Boschma

et al. 2009), for instance. Second, when looking for other regions as strategic partners in S3, it could also be relevant, besides complementary capabilities, to take into consideration other factors, such as geographical or cultural proximity. That is, once a set of regions has been identified based on their complementary capabilities, a region might prefer to connect to regions that are geographically near, or belong to the same country (so national policy instruments could be adopted), or that share the same language or similar norms and values. We see our paper as a first step to analyse more in detail how other forms of proximity besides cognitive proximity may affect the selection of other regions as potential partners in Smart Specialization policy.

Our study did not look at the role of national and regional institutions. Weak institutions, such as low quality of government, or bonding social capital, could impact negatively on the diversification opportunities of regions, especially in peripheral regions (Rodríguez-Pose and Di Cataldo 2015; Cortinovis et al. 2017). So even when the right regional capabilities and inter-regional linkages would be in place, a weak institutional structure might still prevent a region to diversify in new and promising activities. Moreover, one has to take into consideration that the degree of political autonomy of regions differs between and within countries in Europe to a considerable degree (Muringani et al. 2018). In Germany, for example, political power is more concentrated at the NUTS1 level (Länder) rather than the NUTS2 regions (Regierungsbezirke). This may have implications for the implementation of Smart Specialization policy more in general, and for the capacity of regions to link to other regions in particular.

Finally, there is a need to explore how the role of inter-regional linkages can be incorporated in the design and implementation of S3 (Uyarra et al. 2014; Iacobucci and Guzzini 2016; Sörvik et al. 2016; Santoalha 2018; Barzotto et al. 2019), and what kind of policy instruments might be effective to exploit inter-regional linkages to enhance diversification in European regions (Uyarra et al. 2018; Bednarz and Broekel 2020). In this paper, we restricted our attention to the selection of regions that could act as strategic partners in Smart Specialization policy, based on their complementary capabilities. The next step is to think about the design and implementation of S3 once potential partners have been identified. There might be many mechanisms through which policy could facilitate inter-regional linkages, such as publicly funded collaborative research projects in which partners in different regions are selected based on their complementarities (Uhlbach et al. 2017). This also requires considerations in S3 of how to cope with perceived barriers to collaborations between regions in Europe (Uyarra et al. 2018).

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Appendix 1. Descriptives of the variables

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Period	791,240	3.500	1.118	2	2.8	4.2	5
Entry	655,539	0.108	0.310	0.000	0.000	0.000	1.000
RD	781,576	20.987	19.584	0.000	4.730	32.040	100.000
CL	777,485	1.801	0.494	1.000	1.479	2.000	5.200
NL	791,240	6,091.848	14,654.640	0	164	5,588.5	139,701
GDP	490,595	22.345	9.416	3.650	17.050	26.820	93.380
Pop	672,685	1,831,434.000	1,457,450.000	25,060.400	1,008,866.000	2,308,808.000	11,725,090.000
Pop.Dens	610,460	357.861	872.758	2.660	74.050	296.055	9,813.840