Paper to be presented at the DRUID Academy conference in Rebild, Aalborg, Denmark on January

21-23, 2015

Variety, Economic Growth and Knowledge-Intensity of European Regions: A Spatial Panel Analysis

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Abstract

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State of the art
For long time, economists and geographers have studied the relation between agglomeration externalities and development. However, the concepts of related variety (RV) and unrelated variety (UV) introduced a new perspective for analysing such relation. This new framework considers three main hypotheses: RV is associated with higher employment growth, thanks to knowledge spillovers; UV is associated with lower unemployment growth, due to portfolio effects; specialisation is associated with higher productivity growth, owing to efficiency gains for firms.

Research gap
While empirical research provided general support for these hypotheses, some important aspects have been overlooked. Firstly, most papers focus on the effects of variety and specialisation within single countries, and almost no test was carried out on a wider, e.g. pan-European, scale. Besides, differences in the level of technological progress of regional economies and spatial dependence in the data are not always properly accounted for.

Theoretical arguments

While the theoretical arguments behind the hypotheses on variety and specialisation are rather solid, this framework assumes agglomeration works in the same way in developed and in less developed regions. However, unlike in technologically advanced regions, RV is probably not able to foster employment growth in economies where knowledge-intensive sectors play a limited role, simply because knowledge spillovers are less relevant. Also UV, while assuring higher resilience thanks to greater diversification, might fail to bring about radical innovation where knowledge is relatively scarcely used. Thus, an additional hypothesis is that variety externalities have positive effects only in technology- and knowledge-intensive economies.

Method
The first three hypotheses on RV, UV and specialisation are tested in a panel of 260 European regions between 2004 and 2012. After testing those hypotheses, we split the sample using a technological regime variable in order to discriminate among types of knowledge economies. Doing so, we can test our additional hypothesis and assess whether the effects of RV, UV and specialisation depend on the type of knowledge present in the economy. Besides, in all the regressions we use spatial panel data methods to capture spatial dynamics. The data come from Orbis database by Bureau Van Dijk, Eurostat and Cambridge Econometrics.

Results
The first three hypotheses are not maintained according to our estimates. Unlike, once the technological regime variable is introduced, the picture changes and the fourth hypothesis is confirmed: RV and UV present significant coefficients with the expected sign for knowledge-intensive regions. This suggests that the effects of agglomeration externalities differ according to the level of technological progress and to the knowledge available within the economy. Besides, thanks to the spatial specification, significant spatial effects are found in all the models.

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Jelcodes:R11,O40

Variety, Economic Growth and Knowledge-Intensity of European Regions: A Spatial Panel Analysis

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November 24, 2014

Abstract

Although the theoretical framework on agglomeration externalities and the channels through which they influence the regional economy appears well established, the empirical evidence on their magnitude and impact has been rather ambiguous and inconclusive. Applying the concepts of related and unrelated variety to an interregional European dataset and using spatial panel analysis, this paper provides critical information on the type and functioning of agglomeration externalities in relation to regional heterogeneity in knowledge intensity and innovation. We demonstrate that modeling this regional heterogeneity in a spatial panel setting is a crucial condition for identifying the positive agglomeration effects of (un)related variety on regional growth. The outcomes have substantial implications for European regional policy: we argue that policies should both be conceptually enriched and more empirically informed.

Keywords: related variety, European regions, spatial panel data, agglomeration economies, technological regimes

1 Introduction

Since the work of Marshall [40], scholars have devoted significant attention to agglomeration economies. While the theoretical framework on agglomeration externalities and the channels through which they influence the overall economy are well established [42], the empirical evidence has been ambiguous and inconclusive. As the empirical debate appears to have reached a standstill, the introduction of the concepts of related and unrelated variety has resulted in a promising conceptual and empirical renewal in agglomeration studies [57]. The primary *raison d'être* of these two new concepts is that the dichotomy between specialization and diversification, as predominantly employed in the literature [4], cannot completely capture the complexity of agglomeration externalities. By examining the sectoral composition of the economy and the functional relatedness of various sectors in greater detail, related and unrelated variety provide additional and critical information on the type and functioning of agglomeration externalities. In its basic definition, related variety is conceptually related to innovative renewal, new market exploration and employment growth, while unrelated variety is linked to a portfolio effect that protects a region against unemployment spillovers across sectors [29]. This divides the typical conceptualization of diversity into two distinctive elements that have markedly different outcomes. Besides, traditional and current understandings associate regional specialization and cluster(ing) with productivity growth [35] [30].

Among the aspects that are not properly addressed in this burgeoning discussion are two that we consider in this paper. The first aspect concerns the divergent functioning of (un)related variety agglomeration externalities across European countries. European regional economic policy is becoming increasingly place-based in character, fuelling the need for comparative information on agglomeration externalities in all European regions [3] [42]. Numerous quantitative studies on (un)related variety have focused on regions within a fixed number of countries[1]. Van Oort et al. [55] conducted an initial informative cross-sectional analysis of the impact of related and unrelated variety on economic growth in a selection of European regions. The advantages of a longitudinal analysis using panel data were clearly missed in that analysis, as was a full treatment of spatial dependence in the processes studied. The second innovative aspect of our paper is therefore that it explicitly addresses important spatial dependence and spatial heterogeneity issues. From both theoretical and policy perspectives, the heterogeneity of European regions becomes increasingly important when examining regions through the lenses of innovation policy and smart specialization [28]. The regionally varying degrees of industrial organization and institutional development are crucially related to different levels of technological progress [52]. The effects of specialization and (un)related variety on regional economic growth will therefore be assessed in light of the different levels of technological progress in European regions. The paper will employ spatial panel data models. This relatively new econometric methodology, which to the best of our knowledge has yet to be applied in this field, allows us to estimate not only the coefficients for each variable in the model but also to account for spatial effects in the data.

We conclude that the confirmation of the hypotheses concerning related variety, unrelated variety and specialization regarding regional economic growth, is strongly dependent on the regions technological progress and (general) degree of innovativeness. Without controlling for this spatial heterogeneity, our models

[1] Studies using the conceptualization of related and unrelated variety are reported for The Netherlands [29], the United Kingdom [5], Italy [8] [51] [1] [16] [39], Germany [13], Finland [32], Spain [11] [12] and the US [17] [26].

do not provide convincing evidence for the hypotheses, as we obtain a statistically significant negative coefficient for related variety (regressed on employment growth) and non-significant coefficients for specialization (on productivity growth) and unrelated variety (on unemployment growth). After introducing the regional technological regimes, however, we find that variety externalities have a positive effect on the economic performance of a region but only for areas that are more technologically advanced and better endowed with knowledge and innovation. In line with Hartog et al [32], our paper indicates that the mechanisms of related and unrelated variety are relevant but that embedding in innovative regions ranked highly in terms of knowledge and technological resources is crucial. This means that less knowledge-endowed regions in Europe have fewer opportunities for growth - contradicting the strategic vision that those regions can catch-up by diversifying their economies ([28] p.66).

The remainder of this paper is organized as follows. Section 2 will provide a selective overview of the literature on agglomeration economies, working towards the introduction of the concepts of related variety and unrelated variety on an interregional, European scale. Section 3 describes the hypotheses to be tested and the models and methods that will be used. This is followed by a presentation of the variables and data in section 4. Section 5 is devoted to the discussion of the estimations we obtained from our models. In our conclusion (section 6), we summarize our main findings and use those insights to highlight policy implications and suggest important areas to be explored in future research.

2 Agglomeration economies and the concepts of (un)related variety

Agglomeration economies can be defined as externalities, either positive or negative, emerging from the context in which an economic actor is located. Regarded as one of the most relevant factors explaining the differences in the performance of regional economies, agglomeration economies have been subject to extensive debate both in academia [42] and in policy [2]. The potentially beneficial effects of such externalities play an important role in shaping the location choices of economic actors and their interaction opportunities [22]. Agglomeration economies represent a complex and multifaceted phenomenon, which is difficult to treat both in theoretical discussions and in empirical research [50].

Traditionally, agglomeration externalities have been conceived as either sector-related or urban-related economies of scale. The former are typically named localization externalities, as opposed to the latter, which are referred to as urbanization externalities. Localization externalities derive from the concentration of a sector in a certain area. Theory suggests that as firms belonging to the same sector locate near one another, they accrue important benefits. Using common suppliers and taking advantage of pooled human capital allows these firms to reduce their production and transaction costs, increase their productivity and become more competitive [35]. In addition to being involved in the same production process, these firms belong to the same "cognitive" community, and hence, they can profit from exchanging knowledge and mutual learning opportunities. On a more aggregate level, these dynamics would prove to be beneficial for the regional economy, fostering growth and development.

Alternatively, the effects of urbanization externalities emerge from the variety and diversity of the economic environment [34]. A diverse and densely inhabited setting, such as a metropolitan area, allows knowledge to be recombined substantially more than in specialized areas, thus spurring cross-fertilization of ideas and innovation. Thanks to the geographical proximity of firms from different sectors, cities can innovate more and experience higher growth rates. Beneficial effects associated with urbanization also emerge from cities' wider variety of goods and consumption preferences [31] and from their ability to attract better educated, more industrious and creative individuals [50]. From a policy perspective, a region could benefit and improve its performance by attracting firms from different sectors and fostering diversity within its economy.

The striking contrast between these two lines of argument has fostered a large discussion on whether specialization or diversity is the dominant driving force for regional growth. Despite the numerous empirical studies focused on this issue, the results are indecisive and open to discussion. There are two primary reasons for this plurality of results. First, from a conceptual perspective, while theory sharply distinguishes between localization and urbanization externalities, the reality is much more blurred. As various scholars have observed, specialization and diversity can coexist [23] and cities can also evolve and develop in both respects [48]. Second, from an empirical perspective, Beaudry and Shiffauerova [4] suggest that varying methodologies, levels of aggregation and measurement lead to dissimilar results. This point has also been confirmed by the meta-analyses by Melo and coauthors [44] and De Groot et al [20].

Given the lack of conclusive results in the debate over specialization and diversification, scholars have sought new conceptual frameworks (Van Oort et al. 2014). The ideas and arguments of the evolutionary economic geography (EEG) approach have gained particular attention, especially in light of the importance they attach to knowledge and innovation dynamics as drivers of the evolution of economic systems [10]. Directly referring to a Schumpeterian view of capitalism as a restless system continuously moving and changing itself, scholars of the EEG school consider economies to be subject to constant, endogenous transformation. The evolutionary trajectory of an economy is defined on the basis of its internal features and characteristics. Precisely because of such endogenous change, the intangible assets and characteristics of the economy, such as knowledge and institutions, are crucial in driving its evolution [42]. Moreover, different forms of proximity are important in shaping the evolutionary process of an economy. In this sense, while geographical proximity is essential for collective learning [9], cognitive and cultural proximity are equally important for defining opportunities for knowledge to flow, be recombined, spur innovation and be used in productive processes [7].

The discussion of proximity has clarified that not all knowledge is equal. More "proximate" knowledge, from a cognitive rather than geographical perspective, is important, as it can move and can be recombined more easily across the economy. In this sense, in a highly specialized economy, knowledge will not naturally be recombined, as firms have access to the same pool of technical expertise. This might even lead to a situation of cognitive lock–in. Alternatively, when the cognitive distance between two sectors in a diversified economy is substantial, it is unlikely that knowledge and ideas will be exchanged, as actors in the two sectors will not "speak the same language" [14].

Reconsidering urbanization externalities on the basis of this understanding, Frenken et al. [29] noted that complementarities must exist for knowledge flows and recombination to generate positive results. In their study, sectoral diversity is divided into related variety and unrelated variety to discriminate between sectors in which proximity allows knowledge to move from one sector to another (related variety) and sectors in which ideas and skills are unlikely to spill over (unrelated variety). Each of the two sides of variety has its advantages. Related variety allows firms and organizations to access knowledge from complementary sectors and recombine it into new products or processes [7]. As the level of knowledge-relatedness influences the opportunities for firms to innovate [14], high levels of related variety are likely to have a positive effect on employment, as new goods and products will come into production. However, an economy with highly unrelated sectors will benefit from this diversification, in particular by being better protected against sectoral shocks [29]. At least in the short run, a high level of unrelated variety is thus likely to be associated with lower unemployment growth. From this theoretical understanding, Frenken et al. [29] use data on Dutch regions to empirically assess these relationships. Their framework has found numerous empirical applications, particularly in regional analyses of European countries. In many cases, the results match the hypotheses, especially in terms of related variety, confirming that employment growth increases with high relatedness across sectors. Moreover at a wider, pan–European level, the positive relationship between related variety and employment growth has been demonstrated in a cross-sectional research setting [55].

Certain important issues were not fully addressed in these studies on related and unrelated variety. First, as nearly all of these papers focus on agglomeration economies within specific countries in Europe, the evidence and usefulness for *European–wide* regional development policies is limited. Typically advanced economies, such as those of the United Kingdom, Italy or the Netherlands, are used to test the variety hypotheses. As these are all knowledge–intensive economies, these studies may be biased with respect to where policies may be effective. Moreover, an aspect that is often neglected is the relationship between agglomeration economies and the overall level of economic development [20]. This paper assesses the relationship among variety, specialization and regional growth in a sample of European regions to test whether the hypotheses of Frenken et al. [29] hold in a much more heterogeneous set of economically integrated regions, some of which are more technologically advanced than others.

Second, in their study of Finnish regions, Hartog et al. [32] note that the impact of related variety on growth depends on the type of sectors considered. While, at an aggregate level, they do not find any effect of related variety on employment growth, focusing on (localized) high–tech sectors results in a positive effect. Building on this, we will investigate whether related variety and unrelated variety are important for growth, depending on the level of innovativeness and technological progress of the regional economy. The intuition is that externalities associated with knowledge spillovers and the introduction of innovative ideas are much more relevant in regions characterized by a knowledge–intensive economy.

Third, while most of the research on agglomeration economies explicitly mentions spatial spillovers [18] [41] [11], few studies resort to spatial econometric models to fully account for spatial dependence in the data [55] [5]. In our analysis, we will use full spatial panel modeling, assessing whether spatial dynamics are present and controlling for spatial dependence that would otherwise make our estimates biased and inconsistent [36].

3 Hypotheses and econometric models

To address these three issues, we will apply and extend the framework of hypotheses advanced by Frenken et al. [29] on a European level and employ a spatial panel approach. Specifically, the hypotheses we test are the following:

- **Hypothesis 1:** related variety and employment growth are positively related due to knowledge spillovers across sectors and innovation dynamics induced by knowledge recombination;
- **Hypothesis 2:** unrelated variety and unemployment growth are negatively related, owing to portfolio effects associated with a diversified economy and dampened effects of sector-specific shocks;
- **Hypothesis 3:** specialization and productivity growth are positively related due to the cost-reduction and efficiency gains achieved through localization externalities in specialized regions.

Besides, following the conclusions of Hartog and al. [32], we investigate a fourth hypothesis:

- **Hypothesis 4:** the effects of related and unrelated variety are more pronounced in economies more intensely exploiting knowledge and high technology, due to the greater availability of skills, know-how and human capital in these areas.

These four hypotheses will be tested by applying spatial panel data models using NUTS–2 regions in Europe as observations. To begin, two spatial terms will be included in each model: one accounting for the spatial autoregressive process (i.e., spatial correlation in the dependent variable) and the other to control for spatial autocorrelation (i.e., spatial correlation in the residuals). The model will thus be specified as a spatial autoregressive model with autoregressive disturbances (SARAR). When one of the spatial terms is not significant, the model will accordingly be reduced to a spatial error (SEM) or a spatial lag (SAR) specification [38], following what the literature calls Hendry's methodology [24] [27].

To directly account for geographical proximity, a spatial structure has to be imposed. We achieved this by specifying the spatial weight matrix W. Among the different methods that can be used to construct such a matrix [38], we opt for an inverse distance matrix with a critical cut-off. With d being the chosen cut–off, two regions are considered neighbors if the distance between them (d_{ij}) is lower than d; in this case, the inverse of d_{ij} is used as the entry in the spatial matrix. If two regions are not neighbors, the value in the weight matrix will be zero. As is customary in spatial econometrics [24], the spatial matrix is row-standardized. In mathematical notation:

$$W_{ij} = \begin{cases} d_{ij}^{-1}, & \text{if } 0 < d_{ij} \leqslant d; \\ 0, & \text{otherwise.} \end{cases}$$

The choice of weight matrix was made following the suggestions by LeSage [37], namely to use a sparse connectivity structure and avoid complex decaying functions. With respect to the former suggestion, we introduce a cut–off at 750 kilometers to ensure a high percentage of zero-values (more than 80%) but a distance range that is sufficiently wide to reflect the dynamics of highly integrated regional economies. Ertur and Le Gallo [25] construct European weight matrices with similar ranges using k–nearest definitions of 10, 15, 20 and 25. Concerning the decay function, we take the inverse of the distance between two regions, such that a close neighbor (d_{ix} close to 0) has a greater weight than one located farther away (d_{iz} close to d).

Different models will be applied in our investigation. The first model tests hypothesis 1, and hence it uses employment growth as the dependent variable. The second model tests hypothesis 2 and uses unemployment growth as the dependent variable. The third model tests hypothesis 3 and uses productivity growth as the dependent variable. The formal structure of the models is the following:

$$\begin{aligned} \Delta y_{it} = \alpha_i + \tau_t + \lambda W \Delta y_{it} + \beta_1 y_{it} + \beta_2 RVar_{it} \\ + \beta_3 UVar_{it} + \beta_4 Spec_{it} + \beta_5 Control_{it} + \rho W u_{it} + \epsilon_{it}, \end{aligned} \tag{1}$$

where Δy_{it} is the growth of the employment rate, unemployment rate or productivity between time t and $t+1$ and y_{it} is the same variable expressed in levels at time t[2]. Each of these models contains both individual fixed effects (α_i) and time dummies (τ_t). All models include the three explanatory variables (related variety ($RVar_{it}$), unrelated variety ($UVar_{it}$) and specialisation ($Spec_{it}$)) as well as some control variables ($Control_{it}$). In our spatial specification, $\lambda W \Delta y_{it}$ is

[2]The equation thus represents a simultaneous model. While this might make the estimation problematic, we also estimate a lagged version of the model. As the results do not change between the two specifications and the time dimension is not long, we decided to use the simultaneous version.

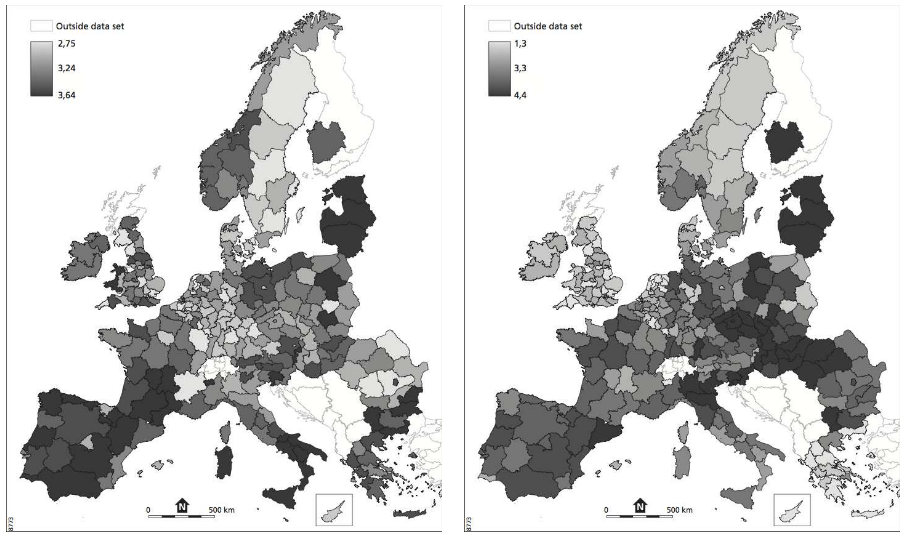
the spatial autoregressive term for the dependent variable, while $\rho W u_{it}$ captures the spatial correlation in the residuals among regions nearby. With respect to Hypothesis 4, the same three models used for the first three hypotheses are re–estimated, but here, the sample is divided into different groups according to the level of technological progress in each region. To create these different regimes, we exploit the categorization of European regions made by Wintjes and Hollanders [58], as discussed in the following section. The technological regimes are interacted with the variables in the models to assess how the variables of interest behave in regions belonging to different regimes. The regressions for each of the technological regimes are estimated simultaneously and the spatial coefficients are common and jointly estimated [6]. In contrast to the first three models, the cross-sectional fixed effects are replaced by the technological regime constants because both individual fixed effects and the regime variable are time invariant. Including both of them would then create collinearity problems.

4 Variables and data

In calculating related and unrelated variety, we applied the same approach as Frenken et al. [29], using two entropy measures calculated on employment shares in 260 regions for 9 years in a panel setting (N=2,340). Detailed sectoral information on the regions is needed to calculate these measures (obtained and aggregated from the firm-level ORBIS database collected by Bureau Van Dijk and discussed below). Using the progressive structure of the NACE classification of these employment data, from broader to finer groupings, we consider unrelated those sectors that belong to each of the 21 different sections of the classification (variation between sections). Simultaneously, detailed sectors *within* each of these sections are considered related to one another, precisely because they belong to the same section (and presumably share consumer and producer markets and production technologies). The choice of using sections as cut-off for between and within level variation is made to capture the greatest amount of relatedness among sub-sectors as possible. For instance, firms manufacturing textile products and firms producing apparel belong to the same section ("C") but to different NACE sub-sectors (divisions 13 and 14, respectively). An approach using divisions to compute related and unrelated variety would have considered these two sub-sectors to be unrelated, while they are actually rather similar.

The method introduced by Frenken and al. [29] takes into account the entropy in the distribution of shares within each level of the industrial classification. Unrelated variety ($UVar_{it}$) is therefore the measure of entropy among the 21 NACE sections and can be calculated as:

$$UVAR_{it} = \sum_{s=1}^{S} P_s log_2 \left(\frac{1}{P_s} \right),$$



(a) Unrelated Variety (b) Related Variety

Figure 1: Unrelated and related variety in Europe

where P_s represent the share of employment in section S over total employment in the region i at time t. In a similar fashion, related variety ($RVar_{it}$) is measured as the weighted sum of entropy within each of the S sections in the classification. More precisely:

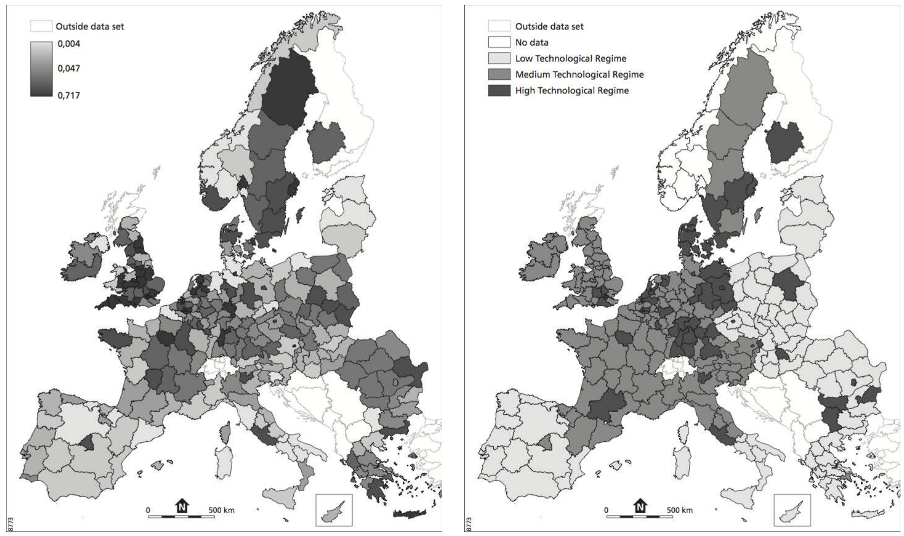
$$RVAR_{it} = \sum_{s=1}^{S} P_s H_s,$$

with

$$H_s = \sum_{d \in S_s} \frac{p_d}{P_s} log_2 \left(\frac{1}{p_d / P_s} \right),$$

where p_d represents the employment share of division d over the total. The maps in Figure 1 reproduce the spatial distribution of related and unrelated variety across the sample in 2004. As the maps clearly indicate, variety at high levels of aggregation exhibits no strong resemblance to variety at low levels, which strongly suggests that the choice of sector aggregation is not trivial. Related variety appears to be a somewhat more *urban* regional feature than unrelated variety (compare [29]), with higher scores in Lombardy, Catalonia, Paris, Hamburg, Munich, and Eastern-European urban regions.

For what concern the specialisation ($Spec_{it}$), we used the Theil index of location quotients of employment shares. The level of sectoral aggregation is,



(a) Specialisation (b) Technological regimes

Figure 2: Specialisation and technological regimes in Europe

again, NACE sections. Location quotients are a measure of relative specialization per sector, i.e., they indicate whether a sector concentrates relatively more or less employment in a region compared with the European average. We computed the Theil index, an entropy index for measuring dissimilarity, to obtain an overall regional measure of relative specialization [19]. Ranging between 0, when location quotients are equally distributed across all sector, and 1, in case of total concentration of employment in one sector, the $Spec_{it}$ variable gives account of the deviations from the European average in the sectoral distribution of employment. While there are many ways to measure specialization[47] [19], this global measure was proved to be a robust estimator in Van Oort et al. [55][3] and Thissen et al. [54]. Figure 2 depicts the spatial distribution of the specialization variable across European NUTS–2 regions in 2004. Urban regions generally appear more specialized than other regions.

As mentioned above, we followed Wintjes and Hollanders [58] to define the technological regimes in our sample. In their analysis, different indicators of employment, human resources, technology, activity rates and the overall economic situation are used to divide EU regions into seven types of knowledge economies[4]. High-technology regional profiles are present in Southern Ger-

[3]While we attempted to ensure comparability between our paper and Van Oort et al. [55], marked differences exist. In particular, while we use employment shares to weight firms in regions and sectors (and controlling for the large-firm bias in the ORBIS data), Van Oort et al. use firm turnover stemming from a related but different database than ORBIS. Further, our sample of regions is considerably larger than that in Van Oort et al. [55]

[4]See the appendix for additional details on the typology and indicators introduced by Wintjes and Hollanders [58].

many, London and the surrounding area, Paris, Toulouse, Scandinavian urban regions and Eastern European capital regions.Following this approach, regions are ranked according to their capacities in terms of knowledge accessibility, knowledge absorption and knowledge diffusion. Building on this, we assign the regions in our sample into three technological regimes ("High technological regime", "Medium technological regime" and "Low technological regime"), as shown in Table 1. The right-hand panel in Figure 2 depicts the spatial distribution of the regime variable in our sample. As the study by Wintjes and Hollanders [58] did not include Norway, we also excluded the Norwegian regions from our econometric analysis. Missing data for Switzerland, Norway, Scotland and parts of Finland also forced us to exclude these regions.

Table 1: Technological regimes and types of region

Technological Regimes	*Type of Region*	*Performance*
High technological regime	Metropolitan knowledge intensive services regions	High absorption capacity
	Public knowledge centers	High accessibility
	High-tech regions	High diffusion, accessibility and absorption capacity
Medium technological regime	Knowledge absorbing regions	Average performance in diffusion, accessibility and absorption capacity
	Skilled technology regions	
Low technological regime	Traditional Southern regions	Below average in diffusion, accessibility and absorption capacity
	Skilled industrial Eastern EU regions	Below average in diffusion and absorption capacity

In addition to the explanatory agglomeration (variety and specialization) variables and the regime variable, we also include the level (y_{it}) of the growth variable as regressor. For the model of related variety, this concerns the employment rate of region i at time t, while for the models of specialization and unrelated variety, gross value added (GVA) per hour and the unemployment rate will be used, respectively. While the use of the employment rate and unemployment rate is rather straightforward, we decided to use GVA per hour, as it represents a more precise measure of productivity that is not influenced by part-time jobs.

The model equation also contains $Control_{it}$, a term that gathers six control variables we included in our regressions. As for the other regressors, the control variables have values for every year from 2004 to 2012. Gross Domestic Product per capita controls for the overall level of economic development, as it is likely to play a role in regions' short-run economic performance. The average wage is included in the regression to account for the level of individual income in the region. Following the literature on agglomeration externalities (e.g., Puga [49]), we introduce a variable for population density to control for the economic size of a region, which might affect regional growth. In a similar fashion, the market potential variable is intended to capture the effects of demand from outside the region. The measure is calculated as the sum of household expenditure in all the other regions inversely weighted by the geographical distance. As supply-side controls, we include variables for the level and quality of human capital among workers, measured as the percentage of the labor force over 25 having completed tertiary education, and the capital-labor ratio, computed as the amount of gross fixed capital formation per employee. Tables 2 and 3 report descriptive statistics. In Table 3, it is important to notice the high correlation between GDP per capita and GVA per hour. For this reason, we decide to only include the latter in the model of specialization to avoid collinearity problems during estimation.

Table 2: Descriptive Statistics

	N	Mean	St. Dev.	Min	Max
Emp. Growth	2,340	0.005	0.023	-0.132	0.098
Unem. Growth	2,340	0.041	0.203	-0.452	1.477
GVA growth	2,340	0.013	0.031	-0.127	0.194
Emp. rate	2,340	0.653	0.075	0.394	0.802
Unem. rate	2,340	0.08	0.043	0.017	0.341
GVA p.h.	2,340	27.432	13.799	2.529	89.387
Spec.	2,340	0.088	0.115	0.003	0.719
RVar	2,340	3.261	0.639	1.29	4.391
UVar	2,340	3.242	0.172	2.639	3.686
GDP p.c.	2,340	23.145	12.268	2.102	97.976
K-L ratio	2,340	10.233	5.055	0.352	37.602
HK	2,340	0.222	0.074	0.064	0.619
Wage	2,340	9.462	1.084	6.467	12.747
Density	2,340	4.985	1.171	1.121	9.19
Markt pot	2,340	9.001	0.468	7.787	11.439

With respect to the data, our sample gathers information on 260 NUTS-2 regions for the period from 2004 to 2012, inclusive. These regions belong to the first 27 member states of the EU and Norway. Some of the regions must be excluded due to either a systematic lack of data (Scottish regions) or changes in the borders of the regions (Finnish regions).

We primarily gather our data from three sources. GVA, the number of hours worked and the control variables, with exception of human capital, are taken from Cambridge Econometrics regional databases. To calculate related variety,

Table 3: Correlation between independent variables

		I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XII
Emp. rate	I	1											
Unem. rate	II	-0.699	1										
GVA p.h.	III	0.532	-0.304	1									
Spec.	IV	0.250	-0.142	0.278	1								
RVar	V	-0.213	0.110	-0.284	-0.398	1							
UVar	VI	-0.300	0.207	-0.236	-0.361	0.247	1						
GDP p.c.	VII	0.598	-0.390	0.852	0.340	-0.264	-0.357	1					
K-L ratio	VIII	0.413	-0.319	0.693	0.175	-0.253	-0.101	0.696	1				
HK	IX	0.390	-0.118	0.532	0.321	-0.202	-0.220	0.561	0.370	1			
Wage	X	0.381	-0.165	0.536	0.155	0.109	-0.193	0.603	0.352	0.437	1		
Density	XI	0.114	-0.081	0.178	0.379	-0.046	-0.309	0.294	-0.013	0.304	0.492	1	
Markt pot	XII	0.381	-0.254	0.431	0.332	-0.108	-0.327	0.463	0.191	0.344	0.473	0.616	1

unrelated variety and specialization, we used the detailed firm-level information available from the ORBIS database compiled by Bureau Van Dijk. Finally, the employment rate, unemployment rate, human capital and the data on the geographical position of the regions come from Eurostat.

Intensive data cleaning and checking was necessary, especially concerning the (aggregation of) ORBIS data. Although these data have wide coverage, the ORBIS database does not contain information on all firms in Europe - only those reporting annually in yearly reports. Smaller firms are therefore often omitted and simple aggregation of the data would lead to bias. For this reason, we rescaled the values for employment aggregated from the ORBIS data in line with regional employment rates from Eurostat. While this re-addressed the value of the data, it left the proportion of employment across different sectors unchanged, and hence the measures calculated from the data still mirror the sectoral distribution in the ORBIS database. In addition, we used linear interpolation to fill gaps in the data (in particular, those on human capital), which was necessary to ensure a perfectly balanced panel, as required for using the `R` packange `splm` [45].

5 Model estimation and testing

The first part of this section addresses the results concerning the hypotheses on specialization and variety. The second part focuses on Hypothesis 4, stating that agglomeration externalities have differential effects across different regional technological regimes.

5.1 Fixed effects spatial panel models

The results of the spatial panel data models with fixed effects, used to investigate the first three hypotheses, are shown in Tables 4, 5 and 6. In each table, the second column reports the coefficients for each variable, while the third and the fourth columns indicate the significance level. In addition to the coefficients, statistics and tests are included in each table. In particular, we indicate the scores and significance of the spatial specification tests derived by Debarsy and Ertur [21]. The aim of these tests is to select the most suitable spatial specification given the data and the spatial weight matrix. With the same notation as in, we perform likelihood ratio (LR) tests on the following null hypotheses [5]:

- *Joint test*: LR1 tests whether both $\lambda = \rho = 0$;
- *Marginal tests*: LR2 (and LR3) tests whether, assuming $\lambda = 0$ (or $\rho = 0$), $\rho = 0$ ($\lambda = 0$);
- *Conditional tests*: LR4 (and LR5) considers if, given $\rho \neq 0$ (or $\lambda \neq 0$), $\lambda = 0$ ($\rho = 0$).

Model 1 – Related Variety and employment growth The first model – presented in Table 4 – analyzes the relationship between related variety and employment growth. We hypothesize that these variables are positively related. The results of our model contradict this hypothesis, as the coefficient of related variety is negative and significant. This implies that higher scores on related variety are associated with lower rather than higher employment growth. Among the other variables, employment rate and GDP per capita have positive and significant coefficients, implying that regions with higher employment and development levels tend to experience higher employment growth. The same applies to the variable for the capital-labor ratio, the coefficient of which highlights the positive and significant relationship between capital endowment and employment growth. Additionally, we notice that the SARAR specification we adopt is correct according to our tests. The model captures the spatial dimension of the data, with both the spatial autoregression and autocorrelation terms being positive and significant. This result indicates that better performing regions tend to be located near one another [38].

Model 2 – Unrelated Variety and unemployment growth The second model focuses on the relationship between unrelated variety and unemployment growth. In line with the reasoning of Frenken and al. [29], we would expect

[5] These tests are performed sequentially from LR1 to LR5. Using the joint test, we assess whether any significant spatial effect is present, against the hypothesis that both λ and ρ are 0. Through the marginal tests, we consider whether the spatial effects captured by the joint test are due to only one of the spatial terms, under the assumption that the other is not statistically different from 0. Finally, when the marginal tests indicate that at least one of the spatial terms is different from 0, we assess whether the other also has a non-zero coefficient using the conditional tests.

Table 4: Model 1 – Related Variety and employment growth

	Estimate	$Pr(>\|t\|)$	
λ	0.249	0.059	.
ρ	0.612	0.000	***
Empl. rate	0.214	0.000	***
GDP p.c.	0.003	0.000	***
Density	0.021	0.431	
K-L ratio	0.001	0.000	***
HK	-0.028	0.292	
Wage	-0.008	0.424	
Markt pot	0.094	0.338	
RVar	-0.015	0.001	***
Spec.	0.002	0.87	
UVar	0.015	0.116	
N		260	
T		9	
Time dummies		YES	
R^2		0.500	
LR 1	62.927	0.000	***
LR 2	46.140	0.000	***
LR 3	54.83535	0.000	***
LR 4	16.500	0.000	***
LR 5	7.804	0.020	*

The significance levels are codified as follows: $*** < 0.001$; $** < 0.01$; $* < 0.05$; $. < 0.1$

a negative coefficient on unrelated variety, as higher unrelatedness should reduce the effects of sector-specific shocks. As reported in Table 5, the coefficient on $UVar$ is indeed negative but not significant. The model yields a positive significant coefficient for $RVar$. Variables associated with economic conditions, such as unemployment rate and GDP per capita, reveal that regions with higher unemployment tend to experience higher unemployment growth, unlike regions with higher GDP per capita. It is also worth noting that population density, often considered a proxy for urbanization economies, has a negative and significant impact on unemployment growth. The model detects the existence of positive spatial correlation in both the dependent variable and in the residuals, and the Debarsy and Ertur tests [21] confirm that the SARAR specification is the correct one.

Table 5: Model 2 – Unrelated Variety and unemployment growth

	Estimate	$Pr(>\|t\|)$	
λ	0.257	0.003	**
ρ	0.740	0.000	***
Unem. rate	3.189	0.000	***
GDP p.c.	-0.016	0.000	***
Density	-0.788	0.001	**
K-L ratio	0.000	0.867	
HK	-0.304	0.191	
Wage	0.979	0.000	***
Markt pot	-0.895	0.316	
RVar	0.092	0.016	*
Spec.	-0.030	0.731	
UVar	-0.069	0.403	
N	260		
T	9		
Time dummies	YES		
R^2	0.496		
LR 1	42.660	0.000	***
LR 2	18.737	0.000	***
LR 3	21.538	0.000	***
LR 4	23.472	0.000	***
LR 5	20.671	0.000	***

The significance levels are codified as follows: $*** < 0.001$; $** < 0.01$; $* < 0.05$; $. < 0.1$

Model 3 – Specialisation and productivity growth The third model, presented in Table 6, is intended to investigate the relationship between specialization and productivity growth, which is expected to be positive. Our estimations indicate that none of the main explanatory variables has a significant coefficient. Nonetheless, it is worth noting that the coefficients of both specialization and unrelated variety are positive but only marginally insignificant and that $K - L$ *Ratio* and $Wage$ are positive and significant, as we would expect. In addition, GVA per hour is also positive and significant, which implies that regions with higher levels of productivity tend to experience higher productivity growth. Finally, with respect to the spatial specification, both our estimates and the likelihood ratio tests indicate that the SARAR specification is not adequate. While our tests reveal the existence of spatial effects (the LR1 test rejects H0), the most suitable specification cannot be determined. Therefore, as the spatial lag term (λ) did not produce a significant coefficient, we opted for the Spatial Error Model (SEM) specification, which is reported in Table 6.

5.2 Spatial panel models with technological regimes

The failure to confirm the hypotheses of the first three models may be explained by spatial heterogeneity within the sample. Introducing technological regimes might help to control for such heterogeneity and allows us to test Hypothesis 4. However, this implies certain changes to the sample, specification and tests. As mentioned above, Norwegian regions are excluded from these analyses, and rather than regional fixed effects we now apply regime fixed effects. With respect to the spatial specification, we retain those identified in the previous paragraphs, as the data-generating process did not change. Instead of testing the spatial form of the models, we use a Chow-Wald test to determine whether the coefficients in the models with regimes are different from a simple"pooled" model [6].

Model 4 – Related variety and employment growth in a regime setting Table 7 reports the results of the estimates from the model on related variety and employment growth. The Chow-Wald test applied to the model with the three regimes yields a significant result, suggesting that the inclusion of the regimes captures heterogeneity in the sample. As in the fixed effect model discussed above, the SARAR specification produced significant coefficients on both the spatial lag and the spatial error term. With respect to the three variables of interest, the model captures significant differences across the three regimes. We note that the coefficient of related variety is positive and significantly related to employment growth in the regions belonging to the high technological regime, while it is negative and significant for the low-technology regions. In this latter regime, unrelated variety has a negative coefficient. This model clearly highlights how the effects of related variety differ according to regions levels of technological progress: high levels of related variety in regions poorly endowed with knowledge and technology not only may fail to produce effects (as in the case of the medium-technology cluster) but might actually be detrimental to

Table 6: Model 3 – Specialisation and productivity growth

	Estimate	$Pr(>\|t\|)$	
λ	-	-	
ρ	0.648	0.000	***
GVA p.h.	0.007	0.000	***
GDP p.c.	-	-	
Density	-0.019	0.626	
K-L ratio	0.002	0.000	***
HK	0.001	0.987	
Wage	0.046	0.000	***
Markt pot	-0.081	0.581	
RVar	0.004	0.545	
Spec.	0.024	0.119	
UVar	0.023	0.106	
N		260	
T		9	
Time dummies		YES	
R^2		0.382	
LR 1	6.437	0.040	*
LR 2	2.714	0.257	
LR 3	0.726	0.696	
LR 4			
LR 5			

The significance levels are codified as follows: $*** < 0.001$; $** < 0.01$; $* < 0.05$; $. < 0.1$

employment growth. In contrast, regional economies with a strong focus on knowledge-intensive and innovative sectors benefit from sectoral relatedness in the form of employment growth.

Table 7: Model 4 – Related variety and employment growth in a regime setting

	Low tech regime			Med tech regime			High tech regime		
	Estimate	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$	
λ				0.443	0.003	**			
ρ				0.520	0.000	***			
Constant	-0.128	0.001	***	-0.046	0.157		0.002	0.954	
Emp. rate	0.037	0.007	**	0.032	0.027	*	0.019	0.280	
GDP p.c.	-0.001	0.051	.	0.000	0.983		0.000	0.813	
Density	0.003	0.013	*	0.000	0.751		0.001	0.190	
K-L ratio	0.001	0.006	**	0.000	0.016	*	0.000	0.178	
HK	0.061	0.000	***	0.016	0.160		0.066	0.000	***
Wage	0.017	0.000	***	0.002	0.486		-0.003	0.120	
Markt pot	0.002	0.132		0.001	0.408		-0.001	0.180	
RVar	-0.004	0.040	*	0.000	0.795		0.004	0.022	*
Spec.	-0.012	0.512		-0.005	0.415		-0.003	0.657	
UVar	-0.018	0.001	***	-0.001	0.812		0.001	0.930	
N				253					
T				9					
Time dummies				YES					
R^2				0.230					
Wald test				174.540	0.000	***			

The significance levels are codified as follows: $*** < 0.001$; $** < 0.01$; $* < 0.05$; $. < 0.1$

Model 5 – Unrelated variety and unemployment growth in a regime setting The results from the model on unrelated variety are presented in Table 8. The Wald test also supports the statistical significance of the regimes in this case. The positive and significant coefficients of the spatial terms confirm the spatial pattern observed in Model 2. Regarding the estimated coefficients for the variables of interest, unrelated variety is statistically insignificant in the high- and low-technology regimes, while it is positive and significant for the medium-technology regime. A negative and significant coefficient is instead obtained for related variety in the case of high-tech regions; a positive and significant coefficient is observed for regions in the low-tech group. Again, these results indicate that differences in the level of technological development are associated with different effects of agglomeration externalities.

Table 8: Model 5 – Unrelated variety and unemployment growth in a regime setting

	Low tech regime			Med tech regime			High tech regime		
	Estimate	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$	
λ				0.574	0.000	***			
ρ				0.549	0.000	***			
Constant	0.664	0.020	*	0.302	0.279		0.664	0.008	**
Unem. rate	0.655	0.000	***	1.017	0.000	***	0.386	0.067	.
GDP p.c.	0.006	0.026	*	0.002	0.108		0.000	0.830	
Density	-0.004	0.696		0.009	0.228		0.001	0.880	
K-L ratio	-0.002	0.536		0.003	0.061	.	0.002	0.143	
HK	0.135	0.260		-0.248	0.012	*	-0.028	0.822	
Wage	-0.086	0.005	**	-0.061	0.010	**	-0.039	0.036	*
Markt pot	-0.019	0.053	.	-0.005	0.592		-0.002	0.815	
Rvar	0.034	0.030	*	-0.018	0.124		-0.044	0.002	**
Spec.	0.265	0.078	.	0.082	0.083	.	-0.055	0.389	
Uvar	0.002	0.965		0.067	0.049	*	-0.059	0.292	
N				253					
T				9					
Time dummies				YES					
R^2				0.234					
Wald test				106.770	0.000	***			

The significance levels are codified as follows: $***<0.001$; $**<0.01$; $*<0.05$; $.<0.1$

Model 6 – Specialisation and productivity growth in a regime setting
In model 6 (Table 9), we study the impact of specialization on productivity growth across the three different regimes. The Wald test again suggests that the model with technological regimes is significantly different from a model with no regime. The main variable of interest, specialization, does not exhibit any statistically significant relationship with growth across the three regimes, comparable to the version of this model with individual fixed effects. However, the coefficients for related and unrelated variety exhibit remarkable significance.

The former has a positive effect on productivity in both low- and high-tech regions; further, the latter is associated with productivity growth, but only in the high technological regime.

Table 9: Model 6 – Specialisation and productivity growth in a regime setting

	Low tech regime			Med tech regime			High tech regime		
	Estimate	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$		*Estimate*	$Pr(>\|t\|)$	
λ				-	-				
ρ				0.663	0.000	***			
Constant	0.096	0.064	.	0.033	0.480		-0.045	0.303	
GVA p.h.	0.000	0.375		0.000	0.041	*	0.000	0.083	.
GDP p.c.	-	-		-	-		-	-	
Density	0.001	0.590		0.001	0.667		0.002	0.148	
K-L ratio	0.001	0.141		0.000	0.709		0.000	0.742	
HK	0.019	0.359		0.015	0.368		0.036	0.091	.
Wage	-0.009	0.086	.	-0.003	0.433		-0.002	0.525	
Markt pot	-0.001	0.465		-0.002	0.243		-0.002	0.073	.
Rvar	0.012	0.000	***	0.001	0.412		0.006	0.022	*
Spec.	-0.025	0.355		0.007	0.391		-0.003	0.760	
Uvar	-0.007	0.324		0.004	0.460		0.022	0.009	**
N				253					
T				9					
Time dummies				YES					
R^2				0.234					
Wald test	119.830			0.000			***		

The significance levels are codified as follows: $*** < 0.001$; $** < 0.01$; $* < 0.05$; $. < 0.1$

6 Conclusions

This paper investigated the effects of different types of agglomeration economies in relation to regional economic growth. We devoted particular attention to hypotheses introduced by Frenken et al. [29] concerning related variety, unrelated variety and specialization. This study is the first to apply such an analysis to European regions using a spatial panel estimation approach. We are interested in the questions of whether empirical evidence previously obtained at the country level holds on a European scale and whether the endowment of technological and knowledge resources in the economy influence the functioning of agglomeration economies, as suggested by prior research [32]. To determine this, we introduced variety and specialization hypotheses that are tested using a panel of 260 NUTS-2 regions in Europe, including both highly developed economies (Germany, Sweden, the UK) and less advanced ones (Bulgaria, Romania, Greece, Southern Italy). Second, the impact of variety and specialization is studied in three technological regimes, defined according to the levels of technological progress and knowledge intensity of each region. Finally, the models are estimated using advanced spatial panel data models to capture and control for spatial dynamics in the data. Table 10 provides an overview of the six models presented in this paper.

Table 10: Synopsis of the results

Fixed-effects models									
		Model 1			Model 2			Model 3	
Related Variety		**-**			**-**			**NS**	
Unrelated Variety		**NS**			**NS**			**NS**	
Specialisation		**NS**			**NS**			**NS**	
Models with technological regimes									
		Model 4			Model 5			Model 6	
Tech. Regimes	Low	Med	High	Low	Med	High	Low	Med	High
Related Variety	**-**	**NS**	+	+	**NS**	**-**	+	**NS**	+
Specialisation	**NS**	**NS**	**NS**	+	+	**NS**	**NS**	**NS**	**NS**
Unrelated Variety	**-**	**NS**	**NS**	**NS**	+	**NS**	**NS**	**NS**	+

In the table, "+" stands for a positive and significant coefficient, "-" for a negative and significant one, while "NS" refers to non-significant coefficients.

As the top panel of Table 10 indicates, in the first three models we found no empirical evidence to support the hypotheses concerning related variety, unrelated variety and specialization. While the models for the last two variables did not produce any significant results (models 2 and 3), we found that related variety is inversely related to employment growth (Model 1) and positively related to unemployment growth (Model 2). However, once we introduced technological regimes, the relationships changed drastically. For regions in the top technological regime, higher related variety is associated with higher employment growth, lower unemployment growth and higher productivity growth. For these same regions, unrelated variety is also positively related to productivity growth. In the other two regimes, the results are less clear: low-tech regions only benefit from related variety in terms of productivity growth; conversely, for the medium-technology regime, we obtained generally insignificant results, apart from specialization and unrelated variety that appear to be positively related to unemployment growth.

These outcomes add important insights to the growing European diversification, specialization and economic growth debates in both academia and policy. Diversity, and especially related variety, can have a positive effect on growth, but predominantly when the technological and knowledge endowment of the region is high. In other words, agglomeration economies have differential effects across regions in different regimes. The reason may be obvious: externalities associated with knowledge flows only "pay off" in economies that have a high stock of knowledge and technology. Prior research on the impact of related and unrelated variety was unable to longitudinally analyze this on a pan-European scale.

This conclusion bears important policy implications, suggesting that diversification alone is not sufficient to reap the benefits of so-called Jacobs externalities. Investments in human capital, technological upgrading and R&D are preconditions for related and unrelated variety to have beneficial effects on the economy. Our results support the notion that, to be effective, policies must consider the context and the features, such as the knowledge and technological endowment, of any (targeted) region. As agglomeration economies operate differently in different areas, a one-size-fits-all call for diversification and/or (smart) specialization alone is unlikely to be effective everywhere. This may be in contrast with beliefs that smart specialization and diversification strategies[6] may have positive implications for growth in all European regions. As Foray ([28], p.65-66) formulates: "The smart specialization strategy seeks to avoid hindering relative positions between followers and leaders with the less advanced regions being locked into the development of applications and incremental innovations. Of course, smart specialization does not have magical properties to transform laggard into global leaders. However, at the very least, a smart specialization strategy transforms less advanced regions to good followers (...) or even leaders, not in inventing the generic technology but in co-inventing applications. (...) Smart specialization is definitely not only for the best regions; just the opposite. It is a unique stairway to excellence for less developed and transition regions". Our outcomes suggest otherwise - although functional and economic network relationships between transition and leading regions are much more complex than our spatial econometric panel modeling framework can capture [54].

Therefore, we believe that further investigation is required in this field. While we used spatial econometrics to control for spatial effects, we could not include spatially lagged covariates in our models. The values of our variety and specialization measures are aggregated at regional level and do not provide an indication of what sectors are actually driving the scores. These measures can therefore not be used as spatial regressors, as two similar scores in two neighboring regions might be due to highly different sectoral structures. Addressing this problem might be methodologically challenging, but it could clarify the role of spatial proximity in agglomeration externalities. A second line of research is

[6] Related variety is a key component of smart specialization strategies, see Foray ([28], p.29).

to consider other important sources of heterogeneity, such as differences in the level of institutional quality [52]. Third, incorporating functional and economic network structures into the panel estimations could shed light on productive unilateral and multilateral relationships between leading and lagging regions.

While we observed important differences in the coefficients across technological regimes, disentangling the various factors affecting the functioning of agglomeration economies is critical, especially in terms of policy guidance. In light of the vivid discussion on European regional policies and the weak evidence available thus far, obtaining a better understanding of agglomeration economies and their relationship with spatial heterogeneity would offer critical insights to policy-makers in Europe.

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Appendix 1

The variables used by Wintjes and Hollanders (2011) are grouped into five sets, described below:

- *Employment*: including shares in specific NACE classes for high-tech manufacturing, medium-high tech manufacturing, high-tech services and market services, as well as employment shares in Industry sectors (NACE from C to E), Service sectors (from G to K) and Government sectors (from L to P);

- *Human resources*: including the share of employment in science and technology occupations and the share of the workforce with secondary and tertiary education;

- *Activity rates*: activity rates for females, activity rates for individuals with tertiary education, and the share of long-term unemployed over total employment;

- *Technology*: R&D as percentage of GDP, share of university R&D over total R&D, share of government R&D over total R&D, and EPO applications per million population;

- *Economy*: capital formation as a percentage of GDP, labor productivity in Industry sectors and labor productivity in Service sectors.

These indicators are then used in a factor analysis and reduced to eight factors related to knowledge-economies. The two authors studied these factors through a cluster analysis, allowing them to identify the seven typologies of knowledge-economies into which they classify European regions.