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(Un)Related Variety and Employment Growth at the Sub-Regional Level

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Abstract

Empirical results on the link between growth and diversity in (un)related industries proved to be highly dependent on the specific regional and temporal context. Making use of highly disaggregated employment data at the sub-regional level, we find that higher employment growth in Austria is mainly linked to unrelated variety. However, in-depth analyses by sectors and regional regimes illustrate substantial heterogeneity in the results, mainly driven by the service sector and by a large number of relatively small regions. Thus, our results argue against structural policy conclusions based on assessments across all economic sectors or different types of regions.

Keywords: related variety, specialization, knowledge spillovers, employment growth, structural policy

JEL Codes: D62, J24, O33, R11, R58

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1. Introduction

Given the current economic situation of stagnating economies and rising unemployment in many EU countries, economic policies to strengthen growth and employment appear to be urgently necessary. However, the financial capabilities available for such measures are limited in most countries. An increase in the efficiency of economic policies in terms of growth and employment and an optimization in the choice of policy instruments may help to resolve this dilemma. For the efficiency and efficacy of regional structural and cluster policies, it is important to identify the influence of knowledge spillovers on regional growth.[1] As the diffusion of "tacit" knowledge requires repeated interaction between agents, knowledge spillovers are kept within (narrow) bounds both in geographical and cognitive terms.[2] Thus, agglomeration advantages (and the geographical clustering of players) are undisputedly important for the dynamism of an economy. However, so far, it has been clarified neither in theory nor empirically, which type of agglomeration advantage is decisive for innovation-based economic development.

Yet this very issue is of crucial importance in designing a growth-oriented structural policy, not the least as these policy efforts in most industrialized countries since the 1990s have concentrated on the development of clusters which are designed mostly to utilize (local) specialization advantages in the tradition of *Marshall* (1890). However, if knowledge spillovers occur mostly between sectors because innovation springs chiefly from the application of existing technological solutions to new fields (*Jacobs*, 1969), then growth and employment would best be served by a strongly diversified sectoral structure. Ultimately, knowledge

[1] For a survey of knowledge spillovers and their geographical connotations see, i.a., *Audretsch and Feldman* (1996) and *Feldman and Kogler* (2010).

[2] The intensity of knowledge flows rapidly deteriorates with the geographical distance (for instance *Jaffee et al.*, 1993; *Audretsch and Feldman*, 1996; more recently *Capello and Lenzi*, 2013), as well as with the cognitive distance (*Boschma*, 2005; *Breschi and Lissoni*, 2009) between sender and recipient.

spillovers may primarily occur inter-sectorally (i.e. between branches) but remain mostly between technologically and cognitively "related" branches because knowledge transfer between very different branches is difficult to achieve due to the great cognitive distance between players (*Porter*, 2003; *Frenken et al*., 2007; *Hidalgo et al*., 2007; *Neffke et al*., 2011; *Basile et al.*, 2012). In terms of structural policy this would mean a focus on thematic but cross-sectoral priorities.

This paper contributes to the growing body of literature analyzing whether specialization, related and/or unrelated sectoral variety contribute to (regional) employment growth by focusing on the potential heterogeneity in the effects with respect to different economic sectors (manufacturing, services) and different types of regions (urban, non-urban). In particular, at least to our knowledge, we are the first to test for regional heterogeneity at the sub-regional level (below NUTS 2). Also, we combine several previous approaches to provide the first comprehensive analysis on different effects of (un)related variety on employment growth in manufacturing and services: We include an empirical measure of sectoral relatedness (see *Boschma et al.*, 2012) in addition to the standard measure based on sectoral classification, a set of different spatial econometric models as well as an exploitation of time- and regional-specific factors that are unobservable in the cross-sectional framework chosen by previous studies. We make use of detailed annual employment data for 615 NACE 4-digit sectors from 1995 to 2013 at the level of 81 labor market districts in Austria.[3] The sub-regional level has received little attention in the related previous literature but seems crucial for a successful implementation of place based structural policies, given the steep distance decay of knowledge-spillovers identified in the empirical literature (e.g. *Varga*, 2000, *Capello and Lenzi*, 2013).

[3] In Austria labor market districts correspond mainly to the LAU 1 level. Groups of two to three districts typically form one NUTS 3 region.

Our results reveal that employment in the manufacturing sector mainly benefits from related variety and specialization whereas services profit more from diversity. In addition, we find employment in urban regions to benefit from related variety only, while industrial and peripheral regions profit from both related and unrelated variety. Our results thus provide support for place-based strategies and regionally differentiated structural policies. Further, our analysis of highly disaggregated regional data suggest that empirical results on the relationship between (un)related variety and employment dynamics are – at least to some extent – driven by the choice of the regional level analyzed and by the econometric framework chosen.

2. Related research and research questions

The issue of specialization vs. diversity has spawned a wide range of empirical literature. Building up from pioneering studies by *Glaeser et al.* (1992) and *Henderson et al.* (1995), numerous empirical analyses have since been produced without, *in toto*, arriving at a coherent conclusion. The findings vary by the data sources used, indicators applied, regions studied and economic sectors included (*Van Oort*, 2007; *Baudry and Schiffauerova*, 2009). As a general trend, a negative impact on growth was found more often for specialization than for diversity, a finding which may be caused by "lock-in" effects in specialized structures (*Martin and Sunley*, 2006). Positive growth effects of specialization were found more frequently in studies looking at a higher level of (regional and sectoral) aggregation, while those using more disaggregated data more often identified advantages from diversity. When employment growth was used as an indicator of performance, papers discovering positive effects from diversity (and negative or insignificant influences from specialization) prevail, while studies using productivity or output growth (also) found positive effects from specialization. When differentiating by economic sectors (*Van Stel and Nieurwenhuijsen*, 2004; *Van Oort*, 2007; Bishop, 2009; *Bishop and Gripaios*, 2010), results tended to identify positive economic effects from diversity more frequently in the tertiary sector, while discovering more positive effects from specialization in manufacturing – a result in line with product cycle considerations and service characteristics (*Bishop*, 2009). Altogether, analyses in search of a growth-optimizing focus of structural policy that apply a simple distinction between specialization and diversity are hardly conclusive[4] – a fact reflected in the more recent literature starting with *Frenken et al.* (2007). In this literature the concept of (general) diversity is deconstructed and a differentiation is made between variety in "related" branches ("related variety") and variety in cognitively distant "unrelated" branches ("unrelated variety"). In doing so, related variety depicts potential advantages of knowledge spillovers from different but complementary branches, while unrelated variety indicates possible advantages from a lower vulnerability to asymmetric shocks (i.e. a portfolio effect). Thus, both variables may boost growth, while it is only the first one that represents dynamic advantages from knowledge diffusion.

With respect to employment growth, *Frenken et al.* (2007) find found positive effects from diversity in related sectors in the Netherlands at the NUTS 3 level, but no (statistically significant) effects from unrelated variety or specialization. This result was mostly confirmed for several countries and time periods analyzed (*Boschma and Iammarino*, 2009, for Italian NUTS 3 regions; *Boschma et al*., 2012, for NUTS 3 regions in Spain; *Hartog et al*., 2012, for LAU 1 regions in Finland, but only for relatedness in high-tech sectors). At the level of European NUTS 2 regions, however, *Van Oort et al.* (2015) found positive effects of related as well as unrelated variety, while *Cortinovis and van Oort* (2015) found negative effects for related and

[4] *Baudry and Schiffauerova* (2009) included 67 papers on the topic in their survey, of which some 70% offered empirical evidence for positive externalities from specialization (localization advantages), while 75% produced evidence for external effects from diversity (advantages from sectoral diversity). About half of the studies clearly advocated specialization *or* diversity as growth drivers, while the other papers found positive, insignificant or negative results for their original hypotheses.

insignificant results for unrelated variety. Moreover, using alternative performance indicators, *Frenken et al.* (2007) identified a significant cushioning effect of unrelated variety on unemployment, a finding consistent with portfolio effects of diversity on business cycle variations that should be of particular relevance for post 2008 period.

The influence of related variety appears to vary by sectors. *Bishop* (2009) found that unrelated sectoral variety had no significant effect on employment growth in manufacturing but a significantly positive effect on the service sector at the sub-regional level in the UK. In addition, he identified (counterintuitive) negative coefficients for related variety in both sectors. In a later, more disaggregated analysis *Bishop and Gripaios* (2010) showed that nearly half of the (23) sectors analyzed (mostly market services) benefit from variety in related and/or unrelated sectors. Specialization, on the other hand, was negatively related to manufacturing employment growth, while not showing any effect on jobs in the service sector.

Previous evidence for different effects of related and unrelated variety in different types of regions is restricted to two recent papers at the level of European NUTS 2 regions by *Cortinovis and van Oort* (2015) and *van Oort et al.* (2015) that produce inconclusive results. *Van Oort et al.* (2015) compared regions hosting national capitals or a population of at least 3 million inhabitants to regions with smaller cities. For the latter group they found a significant positive relationship between employment growth and related variety, but a negative one with specialization. For the former group of regions they found no significant impact from variety or specialization. Moreover, differences between the two types of regions were not statistically significant. *Cortinovis and van Oort* (2015) divided the EU NUTS 2 regions into high-tech, medium- and low-tech regimes. While detecting a negative relation between related variety and employment growth in the same year across all regions, they surprisingly found a positive effect of related variety for one (high-tech) and insignificant effects for the remaining two regional regimes when analyzing different regimes for the same set of regions. Unrelated variety, on the other hand, remained insignificant in their analysis across all regions, but was found to negatively affect low-tech regions.

Overall, the above considerations and the mixed empirical evidence lead to three main research questions (RQ) to be addressed in our paper at the sub-regional level:

RQ 1: Does sectoral diversity and/or specialization increase employment growth?

Since knowledge spillovers *between* sectors are typically associated with radical innovations, which in turn generate new products and new markets, positive impacts on employment should emanate mostly from sectoral variety. On the other hand, incremental innovations such as improvements of existing products and production processes – which can be expected to impact on productivity rather than directly on employment – should be boosted mostly by knowledge-spillovers *within* sectors (and hence specialization). As our analysis focuses on employment, we expect a positive relation between growth and sectoral diversity rather than specialization.

RQ 2: Do related variety and/or unrelated variety contribute to regional employment growth?

Knowledge spillovers occur mainly between cognitively "near" (complementary) sectors, because of the incompatible knowledge bases of players from unrelated sectors (*Noteboom*, 2000). Accordingly, with respect to dynamic externalities, related variety should have a greater impact on employment growth than unrelated variety. However, the latter may be beneficial to employment growth as it reduces the susceptibility of a region to asymmetric sectoral shocks.[5]

[5] Thus, unrelated variety should also have the advantage of producing dampening effects on unemployment because of its risk-reducing nature.

RQ 3: Do manufacturing and services benefit from the same or a different "optimal" economic structure with respect to RQ 1 and RQ 2?

A combination of lifecycle effects and the consequently greater heterogeneity of input and output relationships should ensure that the service sector profit more from a diversified economic structure (*Bishop*, 2009). Specialization advantages (if there are any), on the other hand, should generate growth effects mostly in manufacturing, because process innovation and the ability to trade products across distance are more important in manufacturing.

RQ 4: Do different types of regions benefit from the same or a different "optimal" economic structure with respect to RQ 1 and RQ 2?

Given differences in their sectoral compositions, different results can also be expected for different types of regions. Nevertheless it is difficult to formulate a clear ex-ante hypothesis on the direction of such differences, given the countervailing arguments in terms of structure and product cycle: Given their higher degree of tertiarization, it can be assumed that employment in urban regions (analogously to the suggestions in RQ 3) should profit more from the advantages of unrelated variety (and less from specialization and related variety). A product-cycle perspective, on the other hand, leads to contrary expectations: activities in the early stages of the product cycle should profit more from knowledge spillovers between sectors and new technological combinations (and thus from related variety). At the same time, such "early" activities in a product cycle should profit mainly from the location conditions of agglomerated areas. Once the product matures, the optimal location shifts towards the edges of a city and ultimately to the periphery (*Vernon*, 1966; *Duranton and Puga,* 2001). Accordingly, employment growth in agglomerations should benefit more from related variety while more peripheral regions should experience growth effects from specialization and unrelated variety.

3. Data and empirical approach

3.1. Measuring variety

In the empirical implementation, the literature has been dominated by a simple approach to delimit cognitively or technologically "related" sectors. Starting with *Frenken et al. (*2007) "relatedness" has been commonly defined by applying official sector classifications (such as NACE or SIC). Assuming that products and the knowledge base required for their production become increasingly similar with increasing disaggregation, sectors are assumed to be the more closely related the more digits they share in their classification. However, there has been some dissent to this approach (*Ejermo*, 2005; *Bishop and Gripaios*, 2010; *Desrochers and Leppälä*, 2011). Hence, methods have been suggested in recent years that attempt to "measure" relatedness by empirical methods. Most of them are based on information on one specific mechanism for knowledge transmission such as a similar input use in terms of resources (Fan and Lang, 2000) and skills (*Brachert et al*., 2013; *Wixe and Andersson*, 2013), or intersectoral input flows (*Essletzbichler*, 2015) and job switches (*Neffke and Henning*, 2013). A promising alternative seems to be to infer sectoral relatedness (indirectly) from the probability that sectors "co-occur" geographically. This is based on the idea that productions which cluster at a given location draw on similar knowledge bases and capabilities which can be found at this particular location. *Boschma et al.* (2012) use measures based on *Porter's* (2003) empirical cluster delimitation as well as a complex proximity measure based on export data in addition to the traditional sectoral measure of relatedness.[6]

Indicators of economic structure necessarily start out from the distribution of economic activities across sectors. In order to measure sectoral diversity, statistical entropy

[6] The authors find positive growth effects from a variety of related sectors for all three methods, but these effects appear more pronounced when empirical methods are used to identify related sectors (compared to the traditional sector classification approach).

measurements have prevailed. Specifically, a Shannon index as specified below is used to decompose total diversity consistently into variety within ("related") and between ("unrelated") sectoral groups. In the following all indicators on variety are measured by region across sectors and thus provide measures for a given region at a given period.

Traditional measure of sectoral variety

First, in line with the seminal paper by *Frenken et al*. (2007) we identify related variety by assuming cognitive proximity across all NACE 4-digit classes of a particular NACE 2-digit division. Unrelated variety on the other hand, is seen as diversity between sectoral groups (NACE 2-digit divisions). Applying this logic, for each district (*r*) unrelated variety (*UV*) measures the employment distribution between 2-digit divisions as

$$UV_r = \sum_{g=1}^{G} E_{g,r} \ln \frac{1}{E_{g,r}}, \qquad (1)$$

where *g* is the index of 2-digit divisions from 1 to *G*, and E_g is the employment in 2-digit division *g* as a share of the district's total employment. For each district, the value of *UV* ranges from 0 to *ln G*, where *UV*=0 if all employment is concentrated in the same 2-digit division *k* (E_k=1, all other sectors E_g= 0, where $g \neq k$) and *UV=ln G* when employment is equally distributed across the 2-digit divisions ($E_g = 1/G, \forall g$).

Related variety (*RV*), on the other hand, measures the employment distribution between the 4-digit sectoral classes in the 2-digit sectoral divisions for each district (*r*) in two steps. First, diversity is calculated within each 2-digit division:

$$H_{g,r} = \sum_{i=1}^{I} E_{ig,r} ln \frac{1}{E_{ig,r}}, \qquad (2)$$

where E_{ig} is the employment share of a 4-digit class *i* (*i=1…I*) within a 2-digit division *g* to which the 4-digit class *i* belongs. Thereby $H_g = 0$ if all workers in 2-digit division *g* are employed in only one 4-digit class within *g*. In a second step, the information on diversity within each 2-

digit division (H_g) is weighted by the relative size of this 2-digit division g (E_g) in total employment. The sum across all G sectoral groups then provides the measure for the related variety in a given district (r):

$$RV_r = \sum_{g=1}^{G} E_{g,r} H_{g,r}. \tag{3}$$

UV and RV are both components of the overall employment variety (V) in a district, which corresponds to the sum of the 2-digit entropy (UV) and the weighted sum of the 4-digit entropy (RV) within each 2-digit division. Thus, total sectoral variety (V) can be calculated as the entropy across the lowest classification level (4-digit classes):

$$V_r = UV_r + RV_r = \sum_{j=1}^{J} E_{j,r} ln \frac{1}{E_{j,r}}, \tag{4}$$

where E_j (at $j=1 \ldots J$) is employment in the 4-digit class j as a share of total employment in all J 4-digit classes.

Empirical measurement of sectoral variety

Given the weakness of the traditional approach as set out above, we additionally use the approach proposed by *Boschma et al.* (2012) to derive "sectoral relatedness" from foreign trade data using a proximity indicator developed by *Hidalgo et al*. (2007) in the context of product spaces. Accordingly, two products are "related" if there is a high probability that countries which have a comparative advantage in one of the two products will also have a comparative advantage in the other.

If i and j are (export) products, then for a given time period variable φ_{mn} measures the (minimal) conditional probability that a country has a revealed comparative advantage (RCA) in product n when it has such a comparative advantage in product m.

$$\varphi_{mn} = min[P(RCAx_m|RCAx_n), P(RCAx_n|RCAx_m)] \tag{5}$$

The higher the (conditional) probability that both products are exported by a country enjoying a comparative advantage for each, the more related the two products will be. Our calculations are based on disaggregated export data on more than 5,000 products and 232 countries from the UNCTAD Comtrade database. One disadvantage of using trade data is that (internationally) tradable activities (goods) are only part of the overall economy. As there is no sufficient basis for doing the same calculation for the service sector, the proximity approach in our analysis can be used only to identify relatedness in the secondary sector.

Specifically, proximity measures are calculated for the years 2000 and 2007 (as the base years for our econometric estimations) for the 5,109 products at the 6-digit level in the HS classification of the foreign trade statistics.[7] For our application, these HS products were translated to the statistical Classification of Products by Activity (CPA) of the European Economic Community which is compatible with the NACE classification by sectors.[8] Following *Boschma et al.* (2012), two NACE 4-digit classes were assumed to be related when their proximity $\varphi_{ij} \geq 0.25$. This was the case in about 9% of the 4-digit class pairs.[9]

Contrary to the calculation of relatedness by sector classification set out above, this approach allows sectors to belong to several "related variety sets". For each 4-digit class *i* the related variety set (S_d) was defined as the quantity of all other 4-digit classes which have a proximity of $\varphi_{ij} \geq 0.25$ to class *i* (and are thus "related"). Subsequently, we calculated the share of the 4-digit class in the total employment of the secondary sector of a district (p_i) as well as the employment share of the related variety set S_d in the total employment of the

[7] The authors wish to thank Andreas Reinstaller for sharing the requisite database.

[8] Since regional employment data are available only down to the 4-digit class level of the NACE classification, the arithmetic mean of proximity values was computed for all 6-digit units within a 4-digit class.

[9] Alternatively, threshold values of 0.2 and 0.225 were tested as well. The proximity variables contributed most to the statistical model when 0.25 was used as a threshold. The proximity indices obtained at the 4-digit class level show a single-peak distribution with a mean of 0.161 and a median of 0.166.

secondary sector (P_d). Once these shares were computed, entropy within a related variety set (H_d) is calculated as

$$H_{d,r} = \sum_{i \in Sd} \frac{p_{i,r}}{P_{d,r}} ln \left(\frac{1}{p_{i,r}/P_{d,r}} \right). \tag{6}$$

Finally, for each district (r) the measure for proximity-based related variety (*PRV*) is equal to the entropy of all *d* related variety sets (S_d), weighted by their employment shares:

$$PRV_r = \sum_{d=1}^{D} P_{d,r} H_{d,r}. \tag{7}$$

The measure of the proximity-based unrelated variety (*PUV*) was computed analogously, defining a set of unrelated sectors for each NACE 4-digit class *i*, which consists of all NACE 4-digit classes where the proximity measure in terms of *i* is below the chosen threshold value ($\varphi_{ij} < 0{,}25$).

3.2. Data and econometric specification

We use a database provided by the Austrian Public Employment Service (AMS) and the Federal Ministry of Labor, Social Affairs and Consumer Protection which contains data on the number of employees and key employment characteristics at the level of (615) NACE 4-digit classes based on the Austrian social security registry. Data are available for the sub-regional level of labor market districts in Austria for the years 2000 to 2013. Besides the key variables of interest most of the control variables used are derived from this source too.

To analyze the effect of diversity on regional employment dynamics we econometrically specify a linear model for 81 labor market districts and two sub-periods (2000–2006, 2007–2013) that allows for potential spatial dependence in employment growth. The model can be denoted as:

$$\boldsymbol{y_{t+6}} = \boldsymbol{B\alpha} + \boldsymbol{X_t \beta} + \boldsymbol{W X_t \gamma} + \boldsymbol{T}\delta + \boldsymbol{u}, \tag{8}$$

where y is the vector of average annual employment growth during the particular 6-year sub-periods in the 81 labor market districts with $t \in \{2000, 2007\}$. Matrix B contains dummy variables for the districts, matrix X contains the chosen diversity measures and other control variables described below. All variables in X consist of the values for the first year (t_0) in each sub-period (2000, 2007) to mitigate concerns on the endogeneity of the right hand side variables. W is a row-normalized first order spatial contiguity matrix, thus WX is a matrix with the spatially lagged (arithmetic) average values for X in the adjacent districts. This controls for possible geographical spillover effects from the explanatory variables in neighboring districts.[10] T is a dummy variable that takes a value of 0 for observations in 2000–2006 and a value of 1 for observations in 2007–2013. α is the vector that estimates the region-specific (fixed) effects of employment dynamics, β und γ are vectors with the coefficients for own and spatially lagged diversity measures and other control variables, and δ is a scalar for the time-fixed effect that maps general, regionally independent trends of employment dynamics in the two sub-periods. u is the vector of error terms that are clustered at the district level. The inclusion of district-fixed effects catches unobservable region-specific developments. A model on average annual growth rates for two sub-periods of six years is preferred over an exploitation of the full (year-by-year) panel structure of the data because the key variables on sectoral composition change rather slowly over time implying a very low year-by-year variance. Furthermore, such a panel only identifies effects taking place immediately within one year. In addition to the key variables of interest we include a number of control variables for regional differences in employment growth:

Specialization: If knowledge spillovers occur mostly within sectors (*Marshall*, 1890), specialization should affect employment growth by way of intra-sectoral agglomeration

[10] In response to growing criticism of spatial autoregressive models (*Gibbons and Overman*, 2012) our main specifications do not include the spatially lagged dependent variable as a regressor. However, spatial autoregressive models were estimated to check the robustness of our results.

externalities (localization effects). Following *Van Oort et al.* (2015), among others, we include the sum of location quotients of the NACE 2-digit divisions weighted by their employment shares within a district as an explanatory variable in all estimates as an index for specialization and intra-sectoral agglomeration advantages compared to other regions.[11]

Labor force participation rate: Accounting for the activity rate controls for possible labor market convergence at the regional level. This variable measures employment effects which may result from labor force participation generally increasing more rapidly in regions with low activity rates.

Wage level: The average wage level in a district is included to control for general economic convergence. It is expected that employment will, *ceteris paribus*, grow more rapidly in regions with lower economic development (and thus lower wage) levels.

Population density: This variable is used to control for general effects from the spatial agglomeration of economic actors. It thus maps urbanization (dis)economies not linked to the sectoral structure.

Employment share in the secondary sector: This variable controls for effects on employment growth associated with a regions structural orientation (manufacturing vs. services).

Educational level and skill intensities: The share of low-skilled workers (completion of compulsory education only) as well as the proportion of employment in (NACE 3-digit) sectors which (according to a sectoral typology by *Peneder,* 2001, 2003) mainly employ "white-collar" and "high-skill" workers measure human capital affects on regional employment dynamics. The share of employment in such high-skill dominated sectors is calculated

[11] Thus, this indicator is a measure of relative sectoral concentration between regions, while variables on variety measure the diversity of activities within regions.

separately for the secondary and the tertiary sector in order to identify potential differences in the growth effect of high-skill sectors between manufacturing and services.

Factor intensity: Analogously, the proportion of employees in the capital-intensive NACE 3-digit sectors is also based on sectoral typologies (*Peneder,* 2001, 2003; *Mayerhofer - Palme*, 2001). It indicates the influence of different capital (and thus labor) intensities in the economic structure of a given district and is again measured separately for the secondary and the tertiary sector.

To facilitate the interpretation of the estimates as elasticities, the structural variables and all explanatory variables which do not reflect shares were included in the estimations as logs.[12]

4. Econometric results

4.1. Overall employment growth

To start with, we examine the relation between diversity and specialization on the one hand and employment dynamics in the 81 districts on the other across all economic sectors (Table 1). Specifications (1) and (2) test the influence of diversity compared to that of specialization. The results show that a higher general diversity (Variety; *V*) is associated with a significantly higher employment growth, while sectoral specialization – as expected – does not provide any significant explanation for differences in sub-regional employment growth. When we distinguish between related variety (*RV*) and unrelated variety (*UV*), we find that the latter makes a highly significant positive contribution to explaining differences in employment growth. This result remains significant when additional control variables

[12] Note that the transformation to logs implies diminishing marginal returns on variety. While this assumption is supported by recent findings for high-tech industries (*Simonen et al.,* 2015), the signs and significance levels of coefficients for the structural variables remain completely unaffected in our estimations when using levels instead of logs.

(specifications (3) and (4)) and their spatial lags (specifications (5) and (6)) are included. The relation between related variety and regional employment growth is both positive and significant in all specifications too. However, the size of the respective coefficients as well as their level of significance are lower than for unrelated variety, a fact that does not reflect our theoretical expectations at first glance.

Among the remaining control variables, differences in the shares of the (major) business sectors significantly contribute to explain variations in regional employment dynamics: A higher share of the secondary sector is linked to higher employment growth. The share of low-skilled workers in a given district is negatively related to employment growth, but this education indicator is, at most, significant at the 10% level only. The same applies to the wage level as a proxy for the level of economic development. Out of the control variables for differences in factor and skill intensities in the regional economic structure, the only one of (weak) significance is the share of employment in high-skill-dominated sectors in the secondary sector in specification (6). Labor participation rate and population density remain insignificant in all specifications which may be related to a rather low variation over time within districts.

The explanatory power of the model (R^2) increases substantially when the spatial lags of the explanatory variables are included. This underlines the importance of multidimensional spatial spillover effects on employment dynamics at the sub-regional level. The coefficients for the variables of interest, however, are very robust in magnitude and statistical significance against the inclusion of spatial lags.

Table 1: Determinants of regional employment growth across all economic sectors

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	0.3170***					
	(0.1120)					
Related variety (*RV*)		0.0700*	0.0670**	0.0644**	0.0613**	0.0631**
		(0.0375)	(0.0289)	(0.0304)	(0.0267)	(0.0278)
Unrelated variety (*UV*)		0.2610***	0.2580***	0.2410***	0.2700***	0.2270***
		(0.0962)	(0.0863)	(0.0833)	(0.0853)	(0.0762)
Specialization	0.0049	0.0045	0.0025	0.0025	0.0015	0.0024
	(0.0030)	(0.0034)	(0.0044)	(0.0040)	(0.0042)	(0.0034)
Labor participation rate			–0.0412	–0.0409	–0.0438	–0.0620
			(0.0821)	(0.0812)	(0.0767)	(0.0756)
Wage level			–0.0634	–0.0630	–0.0885*	–0.1010**
			(0.0566)	(0.0569)	(0.0464)	(0.0465)
Population density			–0.0051	–0.0023	0.0644	0.0618
			(0.0574)	(0.0542)	(0.0631)	(0.0675)
Employment share of secondary sector			0.0930***	0.0882***	0.0708**	0.0764**
			(0.0330)	(0.0323)	(0.0330)	(0.0335)
Share of workers with compulsory schooling only			–0.1450	–0.1500	–0.2490*	–0.2590*
			(0.0892)	(0.0913)	(0.1330)	(0.1340)
Employment share in capital-intensive sectors, secondary sector			–0.0273		0.0047	
			(0.0184)		(0.0215)	
Employment share in capital-intensive sectors, tertiary sector			–0.0658		–0.0721	
			(0.0431)		(0.0448)	
Employment share in high-skill dominated sectors, secondary sector				–0.0369*		–0.0501**
				(0.0220)		(0.0245)
Employment share in high-skill dominated sectors, tertiary sector				–0.0762		–0.0623
				(0.1030)		(0.1010)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.267	0.270	0.398	0.404	0.547	0.576
Adj. R^2	0.253	0.251	0.354	0.361	0.479	0.513

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level.

4.2. Services

As described in section 2, growth effects deriving from the economic structure appear to vary with product cycle phases, which leads us to expect differences by sector (groups). The result for the tertiary sector confirms the expectation of higher employment growth in diversified sectoral structures. Moreover, it becomes clear that the larger coefficient for unrelated variety (*UV*) compared to related variety (*RV*) found for the economy total (Table 1) is mainly driven by the service sector: As Table 2 reveals, the coefficient for *RV* is significant only in four of five specifications for the service sector, and the significance level does not rise above 10%. On the other hand, *UV* remains highly significant in all specifications and increases in size compared to Table 1. As expected, the specialization proxy remains insignificant in the service sector.

Among the control variables, employment growth in services does not show any significant relation with the labor participation rate and with population density. In addition, the contribution of differences in factor and skill intensity remains limited. The relation between the share of low-skilled employment and employment growth is negative in the service sector too, but is insignificant in contrast to the analysis of all economic sectors (Table 1). The level of economic development measured by the wage level similarly appears to be not relevant for employment developments in the service sector. The sectoral orientation of the regional economy, however, seems to matter more for services than for the overall economy: Employment growth in services is higher in industrially oriented regions than in regions already on the way to de-industrialization and tertiarization. This may be seen as evidence that in an increasingly "hybrid" and servo-industrial production system, a geographical link of complementary manufacturing and (business) services fosters growth.

Table 2: Determinants of regional employment growth in the tertiary sector

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	0.4100** (0.1630)					
Related variety (*RV*)		0.0796 (0.0551)	0.0775* (0.0420)	0.0790* (0.0430)	0.0629* (0.0374)	0.0699* (0.0406)
Unrelated variety (*UV*)		0.3740** (0.1530)	0.3820*** (0.1330)	0.3630*** (0.1190)	0.4000*** (0.1300)	0.3770*** (0.1250)
Specialization	0.0031 (0.0053)	0.0019 (0.0054)	–0.0037 (0.0067)	–0.0036 (0.0060)	–0.0066 (0.0087)	–0.0048 (0.0067)
Labor participation rate			–0.0412 (0.0821)	–0.0409 (0.0812)	–0.0438 (0.0767)	–0.0620 (0.0756)
Wage level			–0.0397 (0.0779)	–0.0335 (0.0818)	–0.0378 (0.0633)	–0.0412 (0.0693)
Population density			0.0094 (0.0900)	0.0126 (0.0938)	0.1200 (0.1020)	0.1130 (0.1180)
Employment share of secondary sector			0.1970*** (0.0531)	0.2010*** (0.0572)	0.1620*** (0.0538)	0.1740*** (0.0582)
Share of workers with compulsory schooling only			–0.1470 (0.1400)	–0.1350 (0.1460)	–0.2280 (0.1820)	–0.1830 (0.1950)
Employment share in capital-intensive sectors, secondary sector			–0.0130 (0.0525)		0.0238 (0.0477)	
Employment share in capital-intensive sectors, tertiary sector			–0.0942 (0.0731)		–0.1300* (0.0668)	
Employment share in high-skill dominated sectors, secondary sector				–0.0265 (0.0357)		–0.0382 (0.0410)
Employment share in high-skill dominated sectors, tertiary sector				0.0126 (0.1390)		0.0707 (0.1350)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.270	0.278	0.436	0.427	0.566	0.546
Adj. R^2	0.256	0.260	0.394	0.385	0.501	0.478

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level.

4.3. Manufacturing

In analyzing employment growth in the secondary sector (comprising manufacturing, mining, energy and construction), we used the "traditional" measures for related (*RV*) and unrelated (*UV*) variety based on the sectoral classification (Table 3) as well as the proximity based measures of diversity (*PRV*, *PUV*) as described in section 3.1(Table 4). In line with theoretical expectations both tables indicate that specialization is of significant importance for job dynamics in manufacturing. As a further contrast to the findings for the overall economy and the service sector general variety and unrelated variety seem to have no effect on secondary sector's employment growth.

A comparison of the results in Tables 3 and 4 reveals the higher quality of measuring proximity by geographical "co-occurrence" through foreign trade data compared to the traditional measurement: while *RV* is insignificant in all specifications (Table 3), at least three out of five specifications using *PRV* (Table 4) show significant results, including specification (6) which has the highest explanatory power (R^2).[13] Also, R^2 is higher in all corresponding specifications when using the empirical (Table 4) as opposed to the traditional approach (Table 3). These findings point to an advantage of structural indicators measuring proximity on empirical grounds rather than by sectoral classification.

[13] In addition, in regressions including both *RV* and *PRV* only the latter remains significant. The results on these regressions are available upon request.

Table 3: Determinants of regional employment growth in the secondary sector
Proximity measure based on sector classification

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	0.1160					
	(0.0944)					
Related variety (*RV*)		0.0244	0.0259	0.0148	0.0377	0.0270
		(0.0343)	(0.0346)	(0.0310)	(0.0368)	(0.0302)
Unrelated variety (*UV*)		0.0774	0.0735	0.0668	0.0482	0.0119
		(0.1240)	(0.1270)	(0.1220)	(0.1350)	(0.1160)
Specialization	0.0079**	0.0080**	0.0090**	0.0104**	0.0108***	0.0121***
	(0.0032)	(0.0036)	(0.0042)	(0.0040)	(0.0041)	(0.0035)
Labor participation rate			–0.0255	–0.0195	–0.1050	–0.1210
			(0.0704)	(0.0778)	(0.0771)	(0.0756)
Wage level			–0.0563	–0.0739	–0.1240	–0.1560*
			(0.0846)	(0.0816)	(0.0866)	(0.0805)
Population density			–0.0515	–0.0535	–0.0374	–0.0536
			(0.0941)	(0.0843)	(0.0990)	(0.0859)
Employment share of secondary sector			–0.0082	–0.0466	–0.0075	–0.0356
			(0.0486)	(0.0519)	(0.0491)	(0.0495)
Share of workers with compulsory schooling only			–0.1480	–0.1680	–0.2670*	–0.3520***
			(0.1350)	(0.1290)	(0.1420)	(0.1320)
Employment share in capital-intensive sectors, secondary sector			–0.0411		–0.0163	
			(0.0590)		(0.0508)	
Employment share in capital-intensive sectors, tertiary sector			–0.0453		–0.0258	
			(0.0915)		(0.1070)	
Employment share in high-skill dominated sectors, secondary sector				–0.0416		–0.0584*
				(0.0345)		(0.0320)
Employment share in high-skill dominated sectors, tertiary sector				–0.3150**		–0.3590**
				(0.1580)		(0.1470)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.048	0.044	0.097	0.174	0.273	0.381
Adj. R^2	0.030	0.020	0.031	0.114	0.164	0.288

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level.

Table 4: Determinants of regional employment growth in the secondary sector
Empirically determined proximity measure

	(2)	(3)	(4)	(5)	(6)
Related variety (*PRV*)	0.0417	0.0681**	0.0807***	0.0372	0.0548*
	(0.0252)	(0.0284)	(0.0267)	(0.0308)	(0.0297)
Unrelated variety (*PUV*)	–0.3100	1.5620	3.6990	–2.3530	0.5640
	(2.4030)	(2.9120)	(2.4340)	(3.3790)	(3.0080)
Specialization	0.0090***	0.0100**	0.0103***	0.0124***	0.0114***
	(0.0032)	(0.0041)	(0.0038)	(0.0042)	(0.0041)
Labor participation rate		–0.0046	–0.0096	–0.0784	–0.1010
		(0.0741)	(0.0840)	(0.0763)	(0.0737)
Wage level		–0.0800	–0.0839	–0.1490*	–0.1660**
		(0.0816)	(0.0769)	(0.0811)	(0.0722)
Population density		–0.0571	–0.0578	–0.0210	–0.0448
		(0.0851)	(0.0770)	(0.0954)	(0.0862)
Employment share of secondary sector		–0.0446	–0.0825	–0.0372	–0.0640
		(0.0460)	(0.0556)	(0.0507)	(0.0567)
Share of workers with compulsory schooling only		–0.2100	–0.2510*	–0.2920**	–0.3870***
		(0.1340)	(0.1300)	(0.1360)	(0.1270)
Employment share in capital-intensive sectors, secondary sector		–0.0296		–0.0193	
		(0.0654)		(0.0539)	
Employment share in capital-intensive sectors, tertiary sector		–0.0643		–0.0203	
		(0.0838)		(0.0975)	
Employment share in high-skill dominated sectors, secondary sector			–0.0690**		–0.0730**
			(0.0329)		(0.0346)
Employment share in high-skill dominated sectors, tertiary sector			–0.2680*		–0.3000**
			(0.1410)		(0.1370)
Regional fixed effects	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	yes	yes
Observations	162	162	162	162	162
R^2	0.079	0.159	0.242	0.332	0.426
Adj. R^2	0.055	0.098	0.186	0.232	0.340

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level.

The negative relation between the share of low-skilled workers and employment growth is, in part, highly significant (contrary to the results for the service sector). This indicates that the availability of adequately skilled workers is of greater importance in manufacturing.

However, at least partly significant in both approaches is a negative relation between employment growth in the secondary sector and the share of workers in high-skill dominated industries. Given the overriding structural change towards technology- and knowledge-intensive activities in Austria, this appears surprising at first glance. Explanations could be labor saving productivity gains in technology-oriented industrial sectors, as well as the (larger) impact of the financial and economic crisis on high-tech industries.

4.4. Regional regimes

By analyzing employment growth across all economic sectors analogously to Section 4.1 but accounting for different types of regions, we calculate separate coefficients for two "regional regimes" using a cluster-based typology for Austrian districts by *Palme* (1995).[14] We interact all explanatory variables with a binary variable separating urban from industrial and rural regions. For illustrative reasons, Table 5 shows only the basic specification (2) and specification (6) which is preferred from the results of Section 4.1. Variables highlighted in dark (light) gray indicate differences in the coefficients for the two regional regimes that are significant at the 5% (10%) level.

In the regime of urban regions and their hinterland, employment growth is significantly positively linked to the level of related variety (*RV*), while the coefficient for unrelated variety (*UV*) does not differ from 0. In industrial/rural regions, on the other hand, both types of variety show a positive and significant contribution to employment growth, although the coefficient

[14] This typology is based on a 3-step multivariate cluster analysis with indicators for the settlement structure and (human) capital endowments as discriminating variables. The results indicate 9 regional types, which *Palme* (1995) subsumed into 3 broader regional groups: "human capital intensive regions" featuring the types metropolis (1 district), large city (4), urban hinterland (9) and medium-sized cities (6), "real capital intensive regions" including intensive industrial regions (16) and intensive touristic regions (8), and "capital extensive regions" featuring extensive industrial regions (15) as well as industrial and touristic peripheral regions (22). The viability of this delineation was checked using recent data with no need for revision at the level of the 3 broader regional groups. The present paper labels human capital intensive regions as "urban regions" and subsumes the two remaining groups as "industrial and rural regions".

for *UV* is substantially larger than that for *RV*. Moreover, in specification (6) the coefficients of the two variety measures differ significantly between the two regimes, confirming our expectation concerning differences in their relation to employment growth by regional types. In contrast, we do not find any significant contribution of specialization in the two regimes, albeit the positive sign of its coefficient for the industrial/rural regime echoes the positive relation found for manufacturing (Section 4.3).

Given these results we conclude that employment growth in urban regions benefits more from a diversified economic structure in related fields, while other regions gain more momentum from a broad sectoral diversity. Assuming that businesses in urban regions are more technology-focused and skill-intensive, these results are also in line with the findings of *Hartog et al.* (2012), which conclude that benefits from knowledge spillovers within related sectors only occur in rather technology intensive sectors.

The differences by geographical regimes also provide a plausible explanation for unrelated variety being more important than related variety in our estimates for total employment growth (Table 1), which was not expected from the theory: given the fact that industrial and rural regions (61 districts) outnumber urban regions and their hinterland (20 districts) in Austria, the relations found for the former group obviously dominate the results of our econometric model in section 4.1, which does not differentiate between regional types. However, the fact that the 20 urban districts represent about 60% of total employment in Austria and also accounted for 60% of total employment growth during the period observed highlights the infeasibility of using a rather undifferentiated (and "spatially blind") model to draw meaningful structural policy conclusions in a regionally heterogeneous setting.

Table 5: Determinants of regional employment growth across all economic sectors
By types of regions

	(2)		(6)	
	Urban regions	Industrial & rural regions	Urban regions	Industrial & rural regions
Related variety (*RV*)	0.1650**	0.0444	0.2160***	0.0529**
	(0.0720)	(0.0330)	(0.0747)	(0.0249)
Unrelated variety (*UV*)	0.0925	0.2850***	–0.3990	0.2380***
	(0.2160)	(0.0864)	(0.3360)	(0.0764)
Specialization	0.0087	0.0037	–0.0079	0.0020
	(0.0154)	(0.0035)	(0.0268)	(0.0043)
Labor participation rate			–0.0240	–0.1350
			(0.1070)	(0.0891)
Wage level			–0.1550**	–0.0966*
			(0.0728)	(0.0551)
Population density			0.4160	0.0489
			(0.2630)	(0.0763)
Employment share of secondary sector			–0.0401	0.0572
			(0.2320)	(0.0376)
Share of workers with compulsory schooling only			–0.6980**	–0.1510
			(0.3410)	(0.1230)
Employment share in high-skill dominated sectors, secondary sector			–0.1460***	–0.0268
			(0.0481)	(0.0249)
Employment share in high-skill dominated sectors, tertiary sector			0.4770	–0.0400
			(0.3560)	(0.1140)
Regional fixed effects	yes		yes	
Time period fixed effect	yes		yes	
Spatially lagged explanatory variables	no		yes	
Observations	162		162	
R^2	0.297		0.648	
Adj. R^2	0.265		0.564	

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level. – Dark gray (light gray) background … difference between regional types significant at 95% (90%) level. Spatially lagged explanatory variables estimated jointly rather than separately for the two regimes due to the limited number of degrees of freedom. Coefficients for both types of regions are estimated in the same equation via interaction terms of the explanatory variables with a dummy variable for the two types of regions.

4.5. Robustness checks

Our analyses included a number of sensitivity tests in order to check the robustness of our results. Some of these robustness checks were about the estimation strategy used: as described in Section 3.2, the use of spatially autoregressive models was heavily criticized recently (*see Gibbons and Overman*, 2012, among others). Yet, we also tested spatially autoregressive models in our robustness checks using instrumental variables methods (*Generalized Methods of Moments – GMM*), whereby we applied the spatial lags of some of the explanatory variables as instruments for the spatially lagged dependent variable. Qualitatively, these alternative approaches did not produce any new results (see Table A1 in the appendix).[15]

In our main specifications district fixed effects were included in order to catch unobservable regional specifics which are not captured by the controls. To test the adequacy of this model, a random effects model was estimated as an alternative (see Table A2 in the appendix). Hausman tests reject the validity of this model at a 1% significance level for all specifications. Our choice of specifications for the main results was thus confirmed also on the basis of these statistical tests.[16]

Further sensitivity tests concerned the use of additional and alternative control variables. The entire set of specifications was also estimated using the squared population density as a further control variable (in addition to the population density *per se*) in order to account for potential nonlinearities resulting from countervailing effects of agglomeration (dis-)economies. Moreover, alternative measures were tested for the variables on structural differences in regional employment.[17] The coefficients for our key variables on variety and

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[15] Note that the coefficients for the spatial lags of related and unrelated variety remained insignificant in all specifications throughout sections 4.1. to 4.4.

[16] We further estimated a model considering the two sub-periods as repeated but independent cross-sections. None of these alternative model specifications were accepted by Hausman tests at any feasible significance levels.

[17] We used the combined (as well as the individual) share(s) of high- and medium-skill (white-collar) dominated sectors as proxies for the knowledge intensity of the regional sectoral structure rather than the share of workers in high-skill-dominated sectors. In addition, as an alternative to the share of workers with no more than compulsory education we tested the shares of workers with secondary as well as tertiary education as proxies for the regional skill structure.

specialization were found to be very robust in magnitude and significance against all these modifications.[18]

5. Discussion and policy conclusions

When looking at the economy total, our empirical findings reveal that related as well as unrelated variety is associated with positive employment dynamics in Austria, whereas sectoral specialization does not yield any growth effect. In addition, our econometric analysis indicates larger effects of unrelated variety for the period of observation (2000 to 2013) when analyzing employment growth across all economic sectors. This finding is in line with recent results by *Van Oort et al.* (2015) for European NUTS 2 regions but seems to contradict those in *Frenken et al.* (2007), *Boschma and Iammarino* (2009), and *Boschma et al.* (2012). Out of these studies, only *Boschma et al.* (2012) exploit regional and sub-period fixed effects as does the present paper to control for effects that are unobservable in a cross-sectional analysis. However, as our results reveal, the omission of regional fixed effects leads to a substantial bias in the results.

A major outcome of our analysis at the sub-regional level of labor market districts is that the links between structural characteristics and employment growth are neither homogeneous across sectors nor across regional types. We illustrate that the results obtained for the overall economy (all economic sectors) are strongly driven by the mechanisms acting in the tertiary sector, with unrelated variety dominating related variety. For the secondary sector we find different results, with employment growth benefiting from specialization and related variety. Estimates based on two different regional regimes showed that the higher employment effect found for unrelated variety is driven by the group of non-urban (industrial and rural) districts. However, the bulk of employment growth in Austria arises in urban regions

[18] The results for these alternative specifications are available upon request.

and their hinterland, where related variety is found to be the key determinant of employment growth. Accordingly, policy implications based on "one-size-fits-all" approaches that do not account for the regional and/or sectoral context appear misleading.

At first glance, our findings for regional regimes seem to contradict our results for the tertiary sector, given the generally advanced state of tertiarization in urban regions. However, our results indicating a distinct (positive) relationship between (un)related variety and employment growth in this sector are again mainly driven by the large number of industrial and rural regions compared to urban regions. In the former, the service sector is much less focused on knowledge-intensive, technology-oriented activities than in the latter. Therefore, structural differences within the tertiary sector between the two types of regions resolve the apparent contradiction: more technology-focused and knowledge-intensive services (which are mainly located in urban regions) benefit more from knowledge spillovers in related sectors (c.f. *Hartog et al.*, 2012) whereas in less knowledge-intensive services, which dominate the tertiary sector in industrial and rural regions, it is the portfolio effect of a broad economic structure that is of particular importance.

Differences between regional types also reveal implications induced by the choice of the regional level analyzed: In our analysis on all Austrian labor market districts, the results are dominated by industrial and rural regions, which are more numerous but less important in terms of their economic clout.[19] The results illustrate the need to carefully address regional heterogeneity when analyzing structural policy issues to understand the mechanisms at work and to provide sound evidence-based policy advice. Thus, a focus on different regional types at a fairly disaggregated regional level seems to be a prerequisite for this goal.

[19] One approach to tackle this problem is the estimation of weighted least square. However, weighting districts by their number of inhabitants or employees did not lead to qualitatively different results (see Table A3 in the appendix).

With respect to methodology, our comparison of different approaches to construct structural indicators confirms that an attempt to identify sectoral "proximity" on empirical grounds outperforms the (common) use of the sector classification for delimitating related sectors. Tested for the manufacturing sector (only), we found more pronounced results for our empirical proximity measure than for the widely used sectoral classification based measure of relatedness. Future research should therefore put more emphasis on refining and applying measures of sectoral relatedness based on empirical grounds.

In an economic policy perspective, our empirical results for the sub-regional level in Austria provide strong arguments in favor of an evidence-based structural policy that emphasizes variety and a further diversification into new fields, but pursues vertical focuses within this broad sectoral development. Such a targeted focusing should be oriented along thematic (and thus inter-sectoral) rather than sectoral lines, at least outside the secondary sector. For manufacturing, our findings also promise success by exploiting intra-sectoral "localization advantages" by means of sectoral specialization. In general, proximity to existing regional strengths ensures that new activities and sectors will be embedded in the economic basis of a region and benefit from local resources and capabilities. This requires a regionally differentiated approach, as implemented by the "smart specialization" approach of the European Union's cohesion policy for 2014–2020 (*McCann and Ortega-Argilés*, 2015). Yet, at the same time the advantages of unrelated variety in economic structures should not be neglected: According to our findings, the portfolio effect of a diverse sectoral setting indeed seems to favor regional robustness and resilience in case of asymmetric cyclical shocks.[20]

[20] We found unrelated variety also to reduce the growth of unemployment through this portfolio effect. This link is much weaker for related variety. In line with the theory, a specialized structure tends increase unemployment. See Table A4 in the appendix for further details.

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Appendix

Table A1: Determinants of regional employment growth: robustness tests (1)
Spatial Autoregressive (SAR) Models for specification (6) in Tables 1 to 4

	(1)	(2)	(3)	(4)
	Total Economy	Services	Manufacturing (Traditional)	Manufacturing (Proximity)
Related variety (*RV*)	0.0687**	0.0910**	0.00698	0.0580**
	(0.0338)	(0.0455)	(0.0324)	(0.0281)
Unrelated variety (*UV*)	0.251***	0.319***	0.0171	3.834
	(0.0768)	(0.120)	(0.121)	(2.697)
Specialization	0.00155	-0.00478	0.00648	0.00350
	(0.00445)	(0.00632)	(0.00406)	(0.00383)
Labor participation rate	-0.0889	-0.0627	-0.0684	-0.0577
	(0.0579)	(0.0786)	(0.0812)	(0.0813)
Wage level	-0.0972**	-0.0207	-0.134*	-0.133**
	(0.0478)	(0.0742)	(0.0764)	(0.0661)
Population density	0.0259	-0.0126	0.000962	0.00474
	(0.0522)	(0.0982)	(0.0853)	(0.0765)
Employment share of secondary sector	0.0876***	0.212***	-0.0258	-0.0549
	(0.0294)	(0.0542)	(0.0518)	(0.0566)
Share of workers with	-0.138	-0.172	-0.189	-0.285**
compulsory schooling only	(0.0927)	(0.138)	(0.143)	(0.135)
Employment share in high-skill dominated	-0.0238	-0.00140	-0.0183	-0.0410
sectors, secondary sector	(0.0239)	(0.0369)	(0.0401)	(0.0376)
Employment share in high-skill dominated	-0.00987	0.0614	-0.257	-0.128
sectors, tertiary sector	(0.107)	(0.145)	(0.161)	(0.134)
Wy	0.364	0.467	0.835*	0.910**
	(0.319)	(0.322)	(0.472)	(0.348)
Regional fixed effects	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no
Observations	162	162	162	162
R^2	0.394	0.443	0.111	0.123
F-test on the identification of *Wy*	15.31	11.13	8.958	14.02
p-value	(0.00409)	(0.0251)	(0.0299)	(0.00722)
F-test on weak identification of *Wy*	11.83	8.914	15.40	12.81
Hansen J-test	6.209	2.134	0.0840	5.716
p-value	(0.102)	(0.545)	(0.959)	(0.126)

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level. Spatial lags of (un)related variety, specialization, and wages used to instrument Wy in the first stage equation.

Table A2: Determinants of regional employment growth: robustness tests (2)
Random effects models for the economy total (Table 1), Hausman specification tests

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	0.0132					
	(0.0134)					
Related variety (*RV*)		0.00682	0.00463	0.00322	0.0000785	-0.00357
		(0.00679)	(0.00724)	(0.00700)	(0.00783)	(0.00751)
Unrelated variety (*UV*)		-0.000475	0.0186	0.0275	0.0265	0.0369
		(0.0208)	(0.0217)	(0.0232)	(0.0222)	(0.0242)
Specialization	-0.00101	-0.000610	-0.0000391	0.000127	-0.000617	-0.000317
	(0.00200)	(0.00212)	(0.00209)	(0.00207)	(0.00205)	(0.00208)
Labor participation rate			0.112***	0.107***	0.108**	0.103**
			(0.0396)	(0.0395)	(0.0477)	(0.0475)
Wage level			-0.0531***	-0.0537***	-0.0752***	-0.0805***
			(0.0184)	(0.0172)	(0.0205)	(0.0201)
Population density			0.00313*	0.00335*	0.00161	0.00125
			(0.00179)	(0.00181)	(0.00204)	(0.00204)
Employment share of secondary sector			-0.00321	0.00122	0.00793	0.0111
			(0.0101)	(0.0103)	(0.0113)	(0.0115)
Share of workers with compulsory schooling only			0.0411	0.0390	-0.0616*	-0.0596
			(0.0285)	(0.0288)	(0.0360)	(0.0367)
Employment share in capital-intensive sectors, secondary sector			0.00787		0.00894	
			(0.00985)		(0.00915)	
Employment share in capital-intensive sectors, tertiary sector			-0.0411		-0.0369	
			(0.0271)		(0.0274)	
Employment share in high-skill dominated sectors, secondary sector				0.00142		-0.00628
				(0.00910)		(0.00884)
Employment share in high-skill dominated sectors, tertiary sector				-0.0792		-0.0555
				(0.0588)		(0.0582)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.0726	0.0721	0.103	0.129	0.193	0.202
Hausman test (H0: R.E.; H1: F.E.)	21.99	22.08	38.95	38.88	59.05	72.37
p-value	0.000	0.000	0.000	0.000	0.000	0.000

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level. Hausman test H1: F.E. models in Table1.

Table A3: Determinants of regional employment growth: robustness tests (3)

Weighted least squares estimation for the economy total (Table 1)

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	0.245 (0.177)					
Related variety (*RV*)		0.0827* (0.0453)	0.0633 (0.0414)	0.0716 (0.0458)	0.0617 (0.0380)	0.0614* (0.0362)
Unrelated variety (*UV*)		0.133 (0.158)	0.138 (0.154)	0.115 (0.134)	0.216 (0.131)	0.162* (0.0925)
Specialization	0.00580 (0.00455)	0.00674 (0.00461)	0.00703 (0.00577)	0.00321 (0.00397)	0.00565 (0.00659)	0.00320 (0.00429)
Labor participation rate			0.00343 (0.0526)	0.00409 (0.0544)	-0.00342 (0.0582)	-0.0636 (0.0504)
Wage level			-0.0123 (0.0708)	0.00549 (0.0667)	-0.0504 (0.0682)	-0.0790 (0.0539)
Population density			-0.0133 (0.0640)	-0.00593 (0.0666)	-0.0178 (0.0747)	0.0344 (0.0703)
Employment share of secondary sector			0.0567 (0.0494)	0.0825* (0.0445)	0.0608 (0.0497)	0.104** (0.0513)
Share of workers with compulsory schooling only			-0.319* (0.174)	-0.311* (0.166)	-0.415* (0.226)	-0.378** (0.171)
Employment share in capital-intensive sectors, secondary sector			-0.0246 (0.0340)		-0.00537 (0.0280)	
Employment share in capital-intensive sectors, tertiary sector			-0.0869 (0.0672)		-0.104* (0.0529)	
Share of employment in high-skill dominated Sectors, secondary sector				-0.0700** (0.0343)		-0.0765** (0.0300)
Share of employment in high-skill dominated Sectors, tertiary sector				0.0785 (0.131)		-0.0216 (0.122)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.119	0.133	0.257	0.283	0.375	0.522
Adj. R^2	0.102	0.111	0.203	0.230	0.281	0.450

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level. Regions weighted by their 2000 proportion of employment in total employment.

Table A4: Determinants of regional unemployment growth (all sectors)

	(1)	(2)	(3)	(4)	(5)	(6)
Variety (*V*)	–0.5160***					
	(0.1630)					
Related variety (*RV*)		–0.0437	–0.0538	–0.0456	–0.0740	–0.0999*
		(0.0735)	(0.0746)	(0.0700)	(0.0665)	(0.0596)
Unrelated variety (*UV*)		–0.6260**	–0.5840**	–0.5630***	–0.5760***	–0.3950**
		(0.2400)	(0.2290)	(0.2100)	(0.2030)	(0.1570)
Specialization	0.0016	0.0060	0.0141	0.0110	0.0129	0.0149**
	(0.0089)	(0.0105)	(0.0102)	(0.0092)	(0.0083)	(0.0070)
Labor participation rate			0.2430	0.2770	0.0465	0.1780
			(0.1770)	(0.1800)	(0.1540)	(0.1510)
Wage level			0.1180	0.1060	–0.0424	0.0012
			(0.1280)	(0.1280)	(0.1210)	(0.1090)
Population density			0.0482	–0.0018	–0.2600	–0.2700
			(0.1600)	(0.1520)	(0.2210)	(0.1980)
Employment share of secondary sector			–0.1050	–0.0923	–0.1850**	–0.2180**
			(0.0992)	(0.1030)	(0.0817)	(0.0843)
Share of workers with compulsory schooling only			0.9120***	0.9320***	0.4320	0.4590*
			(0.3110)	(0.3020)	(0.3170)	(0.2750)
Employment share in capital-intensive sectors, secondary sector			–0.0846		–0.0727	
			(0.0627)		(0.0557)	
Employment share in capital-intensive sectors, tertiary sector			0.1660		–0.0404	
			(0.1440)		(0.1020)	
Share of employment in high-skill dominated sectors, secondary sector				0.1710**		0.1390**
				(0.0722)		(0.0614)
Share of employment in high-skill dominated sectors, tertiary sector				0.2740		0.0956
				(0.2120)		(0.1940)
Regional fixed effects	yes	yes	yes	yes	yes	yes
Time period fixed effect	yes	yes	yes	yes	yes	yes
Spatially lagged explanatory variables	no	no	no	no	yes	yes
Observations	162	162	162	162	162	162
R^2	0.167	0.187	0.351	0.386	0.585	0.667
Adj. R^2	0.151	0.166	0.303	0.341	0.523	0.618

Values in brackets show standard deviation, *** … 1%, ** … 5%, * … 10% significance level. Errors clustered at the district level.