

Wicht, Alexandra; Kropp, Per; Schwengler, Barbara

**Article — Published Version**

## Are functional regions more homogeneous than administrative regions? A test using hierarchical linear models

Papers in Regional Science

**Provided in Cooperation with:**

John Wiley & Sons

*Suggested Citation:* Wicht, Alexandra; Kropp, Per; Schwengler, Barbara (2019) : Are functional regions more homogeneous than administrative regions? A test using hierarchical linear models, Papers in Regional Science, ISSN 1435-5957, Wiley, Hoboken, NJ, Vol. 99, Iss. 1, pp. 135-164, <https://doi.org/10.1111/pirs.12471>

This Version is available at:

<https://hdl.handle.net/10419/230058>

**Standard-Nutzungsbedingungen:**

Die Dokumente auf EconStor dürfen zu eigenen wissenschaftlichen Zwecken und zum Privatgebrauch gespeichert und kopiert werden.

Sie dürfen die Dokumente nicht für öffentliche oder kommerzielle Zwecke vervielfältigen, öffentlich ausstellen, öffentlich zugänglich machen, vertreiben oder anderweitig nutzen.

Sofern die Verfasser die Dokumente unter Open-Content-Lizenzen (insbesondere CC-Lizenzen) zur Verfügung gestellt haben sollten, gelten abweichend von diesen Nutzungsbedingungen die in der dort genannten Lizenz gewährten Nutzungsrechte.

**Terms of use:**

*Documents in EconStor may be saved and copied for your personal and scholarly purposes.*

*You are not to copy documents for public or commercial purposes, to exhibit the documents publicly, to make them publicly available on the internet, or to distribute or otherwise use the documents in public.*

*If the documents have been made available under an Open Content Licence (especially Creative Commons Licences), you may exercise further usage rights as specified in the indicated licence.*



<http://creativecommons.org/licenses/by/4.0/>



# Are functional regions more homogeneous than administrative regions? A test using hierarchical linear models

Alexandra Wicht<sup>1</sup> | Per Kropp<sup>2</sup> | Barbara Schwengler<sup>3</sup>

<sup>1</sup>GESIS - Leibniz Institute for the Social Sciences, Mannheim, Germany

<sup>2</sup>IAB Saxony-Anhalt-Thuringia (IAB Regional in der Regionaldirektion Sachsen-Anhalt-Thuringen), Halle, Germany

<sup>3</sup>Institute for Employment Research of the Federal Employment Agency (Institut fuer Arbeitsmarkt- und Berufsforschung (IAB) der Bundesagentur fuer Arbeit), Nuernberg, Germany

## Correspondence

Alexandra Wicht, GESIS - Leibniz Institute for the Social Sciences, P.O. Box 12 21 55, 68072 Mannheim (Germany).

Email: alexandra.wicht@gesis.org

## Abstract

We investigate whether economic functional regions capture spatial clustering of core economic indicators better than administrative regions. For this purpose, we use hierarchical linear models to measure the degree of homogenization of different regional delineations. Our results for Germany show that economic functional regions tend to capture spatial clustering better than administrative ones. However, a considerable amount of clustering at a lower aggregation level cannot be accounted for by economic functional regions, especially around metropolitan centres. Furthermore, economic functional regions, which depict commuting interrelations well, are less able to capture spatial homogenization than other economic functional delineations.

## KEYWORDS

functional regions, Germany, modularity, regional labour markets, spatial correlation

## JEL CLASSIFICATION

C49; D85; J61; R23

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2019 The Authors. Papers in Regional Science published by John Wiley & Sons Ltd on behalf of Regional Science Association International



## 1 | INTRODUCTION

Functional regions are essential for analysing labour market and economic policy (Van der Laan & Schalke, 2001). These regions are defined as areas with strong commuting and economic activity within and few connections to outside regions (Hensen & Cörvers, 2003). In contrast, administrative units are typically designed for administrative purposes and have historical roots. They therefore neglect spatial interrelations due to commuting and economic patterns. This can lead to distorted statistics when indicators are reported either at the place of residence, such as unemployment, or at the place of work, such as income or gross domestic product (GDP). In Germany, this applies particularly in the case of city-states such as Berlin or Hamburg, which are characterized by high inward commuting flows (Wixforth & Soyka, 2005). Moreover, multivariate analyses based on such interrelated regional data violate an important assumption that underlies any regression analysis, namely, the assumption that all units of the analysis are independent (Anselin, 2003; Arbia, 2001).

In this regard, functional regions—according to the narrow definition by Van der Laan and Schalke (2001)—are assumed to capture in particular the spatial clustering of economic indicators resulting from commuting interrelations. As a result, such economic functional regions can be assumed to be more homogeneous in terms of their economic indicators than administrative regions, because they take into account economic interactions which lead to harmonization processes (see Cörvers, Hensen, & Bongaerts, 2009) for a formalization of the association between harmonization and economic interactions). Although this would be an important issue for regional labour market research and economic policies, it is an assumption that has seldom been tested to date. The study by Cörvers et al. (2009) for the Netherlands is a first attempt to investigate whether functional regions are characterized by more homogeneity within their boundaries and more heterogeneity between regions. They consider regional disparities in income, employment, unemployment and housing prices and find that functional delineations do not outperform administrative ones.

In Germany, there are different economic functional delineations for regional policy and research purposes (cf. section 3). The explanatory power of these regions has not yet been evaluated systematically in the research conducted so far. However, first descriptive statistical results indicate that such regions seem to be more homogeneous in terms of GDP *per capita* or unemployment rates than administrative regions (Kropp & Schwengler, 2016). More precisely, Kropp and Schwengler (2016) show that the standard deviations of these indicators are smaller between the districts within economic functional regions than across all districts.

This paper aims to explore whether economic functional regions are more homogeneous than administrative regions and how well different regionalizations capture the spatial clustering of economic indicators. We draw on intraclass correlation coefficients (ICC) to measure the degree of homogenization or spatial clustering within regions resulting from different delimitations. This is a new methodological approach to our research problem. Measures of ICC are based on hierarchical linear models, which make it possible to evaluate the within-cluster and between-cluster variance even when there is a large number of clusters, as is the case in many functional and administrative regions. Additionally, in contrast to spatial statistical models, these kinds of models can easily be extended to take clustering at multiple regional levels into account. We draw on core economic and labour market indicators at the level of associations of local authorities (LAU 1 – local administrative units in the EU statistics) and compare: (1) two-level models with different regionalizations at a higher level of aggregation; and (2) three-level models that additionally take into account spatial clustering at a lower aggregation level. Furthermore, multivariate analyses allow the use of control variables, which are very important when comparing functional and administrative regions and which in turn vary considerably, for instance in terms of size.

The paper starts by theorizing spatial clustering resulting from spatial interrelations and by discussing the problem of regionalization. Next, we provide an overview of administrative and economic functional regions in Germany. In the subsequent section, we present our data and the statistical methods deployed before reporting the results of our modelling steps. The paper concludes with a discussion of our findings.



## 2 | SPATIAL INTERDEPENDENCIES AND SPATIAL CLUSTERING

Spatial clustering of socio-economic phenomena, such as unemployment, is the result of spatial interrelations between observational units in space, such as points, regions or nations. In other words, one particular observation somewhere on the landscape is dependent on or influenced by one or several other observations on the landscape (Combes, Mayer, & Thisse, 2008; Fujita & Mori, 2005; Krugman, 1991). From this perspective, regional labour market conditions may be mitigated or reinforced by surrounding areas. Such spillover effects (Anselin, 2003) mainly arise due to social interactions (Akerlof, 1997), with the exchange of resources (labour or goods) being the most relevant kind of interaction in this context.

Previous research on mobility at the level of German administrative districts has indeed shown both mitigation and reinforcement processes. On the one hand, labour mobility reduces regional disparities in unemployment (Niebuhr, Granato, Haas, & Hamann, 2012). Similar results have been found for the United Kingdom (Patacchini & Zenou, 2007). On the other hand, there is also strong evidence that selective migration of labour leads to a divergence of regional outcomes: while the migration of low and medium-skilled labour levels out regional disparities in unemployment rates, the migration of highly skilled labour does the opposite (Granato, Haas, Hamann, & Niebuhr, 2015). There are some other studies (Berry & Glaeser, 2005; Kanbur & Rapoport, 2005; Südekum, 2004, 2005; Windzio, 2004) which also confirm that—in contrast to the predictions of neoclassical theory—selective migration may increase regional disparities in wages and unemployment. Although the mentioned literature addresses migration, the same outcomes can be expected with regard to commuting (see Elhorst, 2003 for a discussion on both migration and commuting). From a micro-level perspective, all kinds of spatial mobility are guided by both individual conditions (e.g., skill level, socio-economic resources) and structural conditions (e.g., accessibility, unemployment, employment structure; Cushing & Poot, 2004; Korpi & Clark, 2019). They produce their spatial imprints in terms of both the strength of interrelations between areal units and, as a result, the spatial clustering or dispersion of socio-economic conditions.

When bearing such spatial interrelations in mind, regions should not be regarded as isolated areal units, but rather as components of a broader socio-economic system. This is what Logan (2012, p. 509) has in mind when he writes: "Routinely, social scientists deal with unmarked boundaries." From a methodological point of view, spatial dependencies are reflected in (positive or negative) spatial autocorrelation, which, if neglected, poses statistical problems for any regression analysis (Anselin, 1995). More importantly, spatial dependencies are also of substantial interest for explaining the emergence of regional disparities (Conley & Topa, 2002; Halleck Vega & Elhorst, 2016; Rios, 2017).

Functional regions based on commuting flows are suitable for capturing spatial interrelations between spatial units. Unlike administrative regions, whose boundaries have political and historical roots (rather than socio-economic ones), functional regions permit the detection of spatial clustering. Using Moran's  $I$  statistic (Anselin, 1995), Wicht (2017) demonstrates that the spatial clustering of youth unemployment in Germany can best be depicted by taking into account the commuting flows of apprentices between areal units. In contrast to simple proximity or Euclidean distances, commuting flows reflect that training places are concentrated in centres which draw young people from the surrounding areas. As there are arguments for both homogenization and differentiation, this leads to our first research question:

*Research question 1. Do economic functional regions reveal intra-regional homogeneity better than administrative regions?*

Furthermore, we can distinguish different delineations by means of certain quality measures. The degree of self-containment in terms of strong commuting interrelations within functional regions and weak commuting interrelations between them is such an indicator and is well established in regional science (Coombes, Green, & Openshaw, 1986; Cörvers et al., 2009; Smart, 1974; Van der Laan & Schalke, 2001). However, self-containment on its own is not an appropriate quality measure for functional delineations, as its value increases with the number of unified



regions, with a maximum value of one if all regions are merged. Therefore, Kropp and Schwengler (2011, 2016) suggest using the modularity ( $Q$ ) as a criterion for identifying the best delineation.

The modularity measure was developed to assess clustering in networks (Newman & Girvan, 2004) and compares the weight of links within a cluster with the weight of links that would be expected if a network (i.e., the commuting network between districts or municipalities) were random. Therefore, clustering exists if the number of links in a cluster is greater than the number of links in the null model. This approach yields a network with the same number of nodes in which each node maintains its network degree (i.e., the value of in-going and out-going links), but the links are otherwise randomly distributed. In this way, the random network preserves important structural characteristics of the actual network but serves as a null model. The Newman-Girvan approach can be summarized with the following formula:  $Q = \sum_i (e_{ii} - a_i^2)$ , with  $a_i = \sum_j e_{ij}$  and  $e_{ij}$  representing the flow between  $i$  and  $j$  as a share of all units. A symmetrical interaction matrix of clusters with cells that contain the share of all units rather than the number of units themselves is the starting point for the calculations. Therefore, the entire matrix sums to the value of one. The area outside the diagonal contains the proportion of units that are not contained within clusters (therefore, commuters between labour market regions). The trace of the matrix (the sum of the diagonal cells) reflects the percentage of non-commuters. One important characteristic of the matrix is that the expected cell value can be computed by multiplying the row sum (proportion of non-commuters and out-commuters) by the column sum (proportion of non-commuters and in-commuters). In the symmetric matrix, this product is equivalent to the term  $a_i^2$ . The expression  $e_{ij} - a_i^2$  compares the empirical distribution with the null model. Clustering exists if the observed number of links in a sub-graph (the cluster or labour market region) is greater than the number of links in the null model. The values typically fall between 0.3 and 0.7 in the wide array of areas in which network measures are applied. For commuting data, in which high levels of clustering in agglomerations occur, comparatively higher values can be expected.

Functional regionalizations based on maximizing modularity perform quite well with regard to several indicators of regional coherence, such as the share of commuting, the commuting ratio and the degree of self-containment of functional regions (Kropp & Schwengler, 2016). With this in mind, these considerations suggest our second research question:

**Research question 2.** *Does modularity positively correlate with the degree of homogenization of economic indicators within economic functional regions?*

Bearing in mind the modifiable areal unit problem (MAUP) (Openshaw, 1984; Wong, 2009), which generally states that the results of regional data analyses are highly sensitive to the choice of areal units used, delineations of areal units in general and those of functional regions in particular should be evaluated with regard to two criteria: spatial scale and spatial zoning. While the scale problem refers to the size or scope of the defined areal units, the zoning problem points to the particular configuration of boundaries selected on any given scale. Both dimensions are important (Fotheringham & Wong, 1991; Griffith, Wong, & Whitfield, 2003; Openshaw & Taylor, 1979) and should be considered when comparing administrative and functional regions. This is a research gap; we do not know whether functional regions tackle the issues raised by the MAUP better than administrative regions, or in more general terms, what regional delineations deal best with the MAUP.

For the Netherlands, Cörvers et al. (2009) aim to investigate the issue of spatial zoning in their analyses of the coherence of functional and administrative regions concerning several economic and labour market indicators. They use commuting data at the level of municipalities and apply a delimitation procedure in which the number of functional regions equals the number of administrative regions. The analyses that they present relate to NUTS 1 regions (i.e., four major regions in the Netherlands). Finally, they use ordinary least squares (OLS) regression analyses to compare the explanatory power of these functional regions with those of their administrative counterparts. They do not find substantial differences in income levels between administrative and functional regions, but housing prices do differ in their study for all pairs of regions. In addition, their results show statistically significant differences for employment and unemployment rates for half of the regions analysed. However, there are two



problems with their approach: (i) they do not deal with spatial scale as a substantial problem, thereby neglecting a significant issue for regional analyses; (ii) they define functional regions by using an arbitrary threshold for the number of delineated regions, which is not suitable for capturing the entire interrelatedness of the data. This could explain why they do not find major advantages in the explanatory power of functional regions compared to administrative ones.

If both spatial scale and spatial zoning are considered, areal units cannot be merged into an arbitrarily determined number of (roughly the same sized) regions; delineations of functional regions can differ considerably in terms of size and they can be oversized or undersized to reveal intra-regional homogeneity. At least in Germany, there are delineations of both large and small functional regions. However, it is reasonable to question whether large and small functional regions encompass homogeneous areas equally well. Following Tobler (1970, p. 236), spatial interrelations are much more likely in the case of areal units which are spatially close to each other: “[...] I invoke the first law of geography: everything is related to everything else, but near things are more related than distant things.” This means that social interrelations in terms of labour exchange, for instance, which explain the emergence of spatial clustering of observations, are more likely to occur between those areal units that are close to each other. Results of previous research indicate that lower level aggregations are indeed more homogeneous than higher level aggregations (Cliff & Ord, 1981; Griffith et al., 2003; Lee, Lee, Chun, & Griffith, 2018). However, we will address this question here again for the German case and using a new methodological approach:

**Research question 3.** Are economic functional regions at a lower aggregation level more homogeneous than economic functional regions at a higher aggregation level?

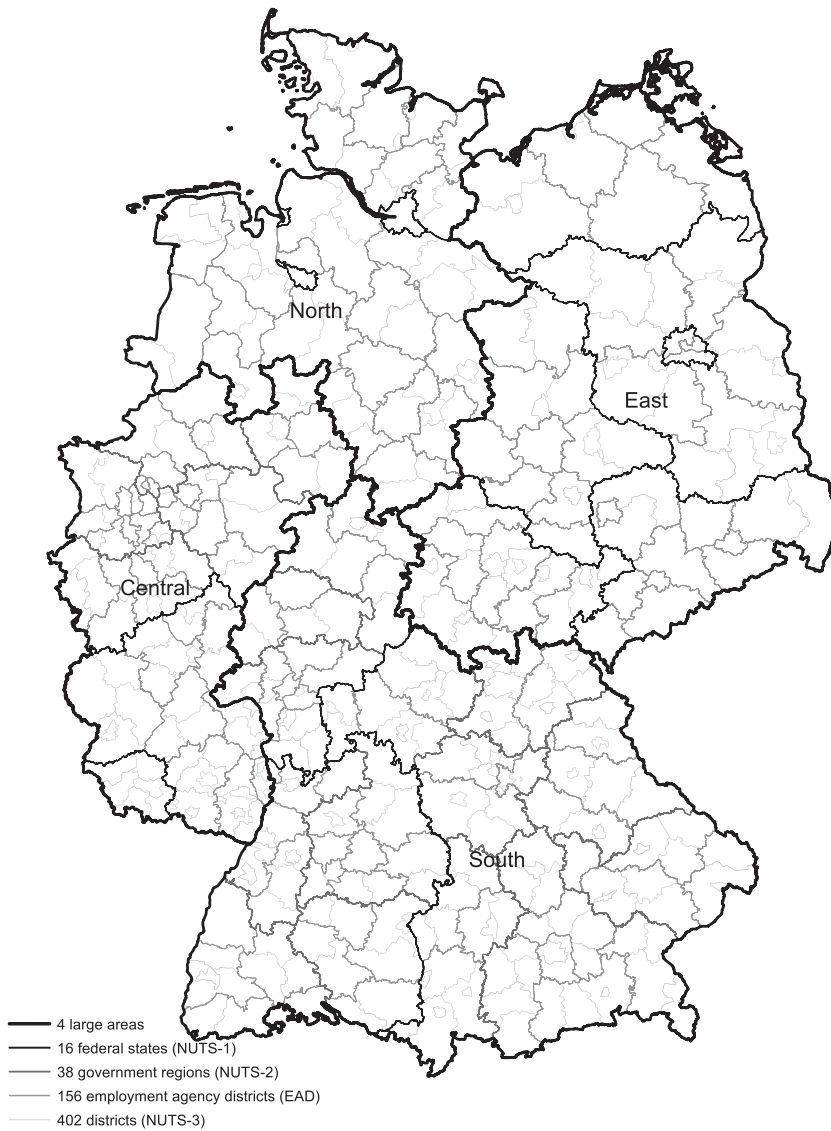
### 3 | OVERVIEW OF ADMINISTRATIVE AND FUNCTIONAL REGIONS IN GERMANY

In Germany, different regional delineations are in use for different purposes. Administrative delineations are the 16 federal states (“Bundesländer”, NUTS 1), which comprise 38 NUTS 2 regions (formerly administrative regions or “Regierungsbezirke”), 401 administrative districts<sup>1</sup> (“Kreise” and “kreisfreie Städte”, NUTS 3) and approximately 11,000 municipalities (“Gemeinden”, LAU 2). These units are the basis for a wealth of official statistics. Furthermore, there are 156 employment agency districts (EAD) of the Federal Employment Agency (“Bundesagentur für Arbeit”, BA)<sup>2</sup> that serve as diagnostic units for labour market policy, for example, for reporting unemployment rates.

At the same time, there are several economic functional delineations that are used for different purposes, for instance for regional policy or regional science. Spatial planning uses the 96 spatial planning regions (SPR) defined by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR) within the Federal Office for Building and Regional Planning (BBR) for their reports. In addition, economic and regional policy has defined 258 labour market regions for identifying regions that are weak or less well developed in structural and economic terms and are eligible for regional aid, for example, from the European Regional Development Fund (ERDF) of the European Union (GWR delineation). Applied science commonly uses 141 regional labour markets (RLM) defined by Kosfeld and Werner (2012). All of these delineations employed in practice are subject to certain constraints and guidelines. Besides these established functional delineations, Kropp and Schwengler (2016) propose a new delineation of only 50 labour market regions (LMR) that are very heterogeneous in size. A more differentiated delineation comprising 105 local labour market regions (LLM) is additionally available. Figure 1 shows four German administrative delineations. The first map in Figure 1 aggregates the 16 federal states of Germany into four large regions, following Frick and Göbel (2008) and shows the hierarchical structure of the different

<sup>1</sup>In our analyses we use data from the year 2014, where the number of districts is 402.

<sup>2</sup>We use 154 regions, as most of the data available for Berlin are for the city of Berlin as a whole and not for the three employment agency district sub-groups within the city.



**FIGURE 1** Administrative regions in Germany

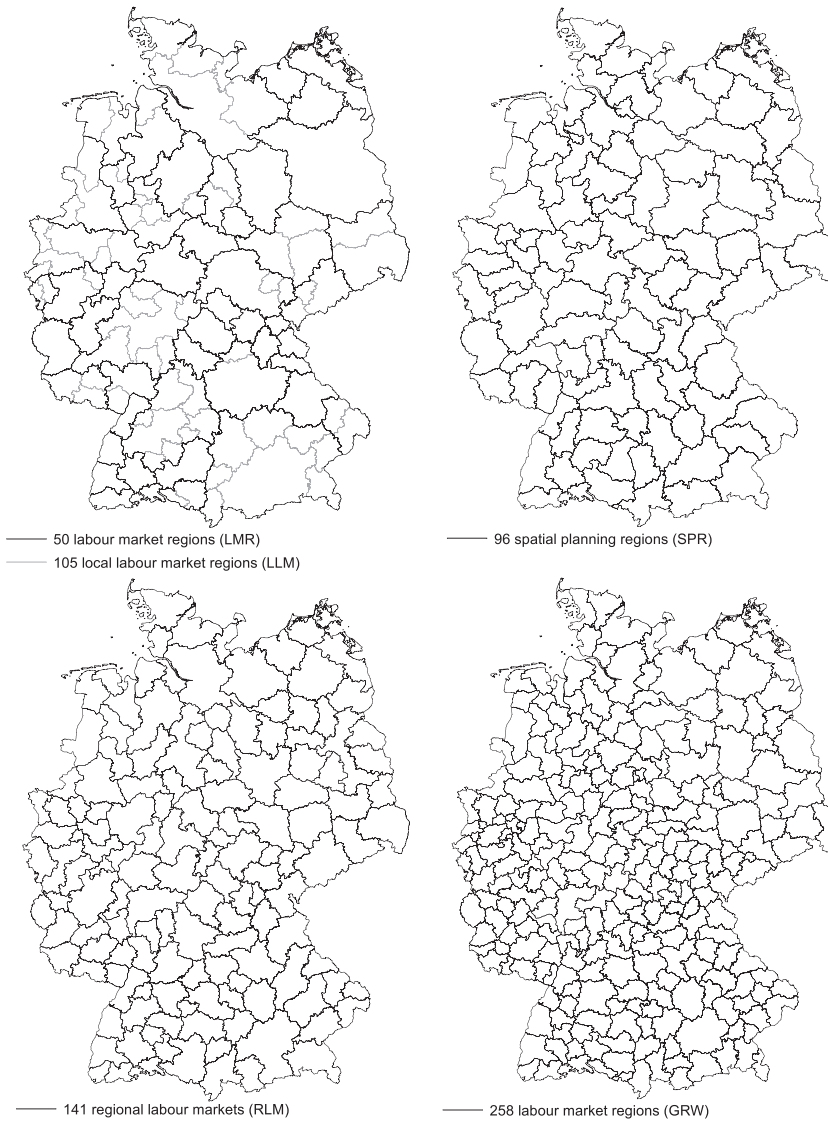
Source: © GeoBasis-DE/BKG, 2014.

German administrative regions. Figure 2 presents the different functional regions that are units of analysis throughout this paper.

## 4 | DATA AND METHODS

### 4.1 | Data

When examining regional disparities in labour market outcomes, researchers commonly base their analyses on four main indicators, considering both short and long-term trends: unemployment and employment rates, income levels and housing prices (Cörvers et al., 2009; OECD, 2016). In our analyses for Germany, we follow this approach but



**FIGURE 2** Functional regions in Germany

Source: © GeoBasis-DE/BKG, 2014.

focus exclusively on short-term indicators. We are unable to present results based on housing prices, as no open-source data are available at the level of municipalities and associations of local authorities. All the data we use are from the year 2014.

The data on unemployment and employment rates are provided by the Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR, 2017), which releases a comprehensive regional time-series dataset annually based on several data sources. Unemployment is calculated as the number of unemployed persons per 1,000 inhabitants of working age, namely, the population aged 15–65. The employment rate indicates the proportion of the resident population aged 15 to under 65 who are in employment subject to social security contributions at their place of residence. Since the employment rate does not include people in marginal part-time employment, civil servants, self-employed persons, family workers or unemployable persons, the unemployment rate and the employment rate are not the inverse of each other. For this reason, their correlation is  $-0.66$  instead of  $-1$ .





To determine the regional income level, we rely on data obtained from the employment statistics of the German Federal Employment Agency (IAB, 2016). At the end of each year, all employers in Germany have to report the wages paid to each employee.<sup>3</sup> The mean wage per region is calculated by dividing the gross wage per year by the number of persons employed in the same year for each region.

In order to investigate the advantages of using economic functional regions rather than administrative regions, we use data at the regional level of 4,453 associations of local authorities, which are clustered within different regional delineations. We use these more homogeneous regions as basic units (or level 1 units) instead of the approximately 11,000 municipalities because German municipalities vary considerably in size.

## 4.2 | Methods

We conduct our analyses with the aid of hierarchical linear models (HLM) (Goldstein, 2011; Rabe-Hesketh & Skrondal, 2012). Like spatial statistical models (Brunsdon & Comber, 2015), HLM are generally appropriate for analysing spatially clustered data, as they make it possible: (i) to correct the standard errors of regression parameters by considering statistical dependencies between observations within regional units at a higher aggregation level; and (ii) to evaluate the within-cluster and between-cluster variance. Furthermore, HLM can easily be extended to take more than two levels into account.

We draw on core economic and labour market indicators (unemployment, employment and income *per capita*) at the basic-unit level and compare: (i) two-level models with different regionalizations at a higher aggregation level; and (ii) three-level models, which additionally consider spatial clustering at a lower aggregation level. In the first step, we estimate two-level random-intercept models with level-1 units (associations of local authorities) nested within different administrative and functional regions. In these models, the mean values of regional units at a higher aggregation level are allowed to differ from one another. The variance estimates of the models can help to reveal the degree to which the different regions pool level 1 units and form homogeneous areal units. For this purpose, we calculate the intraclass correlation coefficient (ICC) based on the variance estimates. The ICC measures the degree of resemblance between level 1 units belonging to the same areal unit at a higher aggregation level. The coefficient is defined as the ratio of the variance between the areal units at a higher aggregation level and the total variance. It expresses the maximum variance which is attributable to the regions at a higher aggregation level and which can be explained by regional characteristics. In other words, the ICC is a suitable indicator of the quality of the delineation of areal units, with high ICC values indicating substantial regional clustering of the values of level 1 units and a high quality of the regional delineation.

In addition, to allow for more local labour market processes, in a second step we calculate three-level models with level 1 units nested within administrative districts (NUTS 3), which are in turn clustered within different administrative and functional regions. We choose administrative districts as the second level because their boundaries correspond with the boundaries of all other regional delineations. Then we compare the models based on ICCs again. This approach enables us to determine: (i) the importance of spillover effects at a lower aggregation level (i.e., between basic units within districts); and (ii) additionally the importance of administrative or functional regions at a higher aggregation level, which may capture remaining spatial interrelations between districts.

In all analyses we use a set of control variables to ensure the comparability of different areal units in terms of the extent to which they can capture spatial clustering. That is essential as administrative and functional regions differ considerably in size (Cörvers et al., 2009). To control for the different sizes, we proceed as follows: first, we take the number of basic units within each regional cluster into account. This number can easily be derived from the

<sup>3</sup>The reported wages are limited to the upper earnings limit for social security contributions. In 2014, this limit was 71,400 euro for employees in western Germany and 60,000 euro for employees in eastern Germany. No contributions have to be paid from wages above this limit.



clustered data. Second, we consider the working-age population, that is, the population aged 15–65 (Statistische Ämter des Bundes und der Länder, 2018). We introduce these indicators at the highest level of aggregation (e.g., labour market regions). Furthermore, we control for four large German areas: East, South-West, Central-West, and North-West (Frick & Göbel, 2008), which are shown in the first map of Figure 1. Neglecting this would lead to an overestimation of the ICCs for all regional delineations, as the four broad areas already capture a large degree of homogenization.

## 5 | RESULTS

### 5.1 | Explorative results

In a first step, we explore the “functionality” of the different delineations in terms of their ability to capture commuting as the main indicator of economic interaction. For this purpose we compare modularity, the percentage of commuters between delineated regions, and the self-containment ratio in Table 1. The pros and cons of these measures were discussed in the paragraphs leading to the second research question above.

Comparing the values of the modularity measure, the delineation comprising 50 labour market regions (LMR) performs best. In addition, the 105 local labour markets (LLM) and the 38 NUTS 2 regions exhibit high modularity values, too. These three delineations yield low commuting ratios as well as high mean values of self-containment. The same holds for the 16 federal states, but with a lower modularity value. Low minimum values for self-containment indicate that a delineation is not functional with regard to capturing commuting interactions. In this respect, GRW and RLM contain at least some regions that have strong commuting relationships with neighbouring regions. In general, economic functional regions in Germany do not always capture economic interaction between regions (as represented in commuting flows) better than administrative regions. This should be taken into consideration when answering our research questions.

In a second step, we explore the overall degree of internal homogeneity of the economic indicators within different functional and administrative regions by using the Global Moran's I statistic (Anselin, 1995; Moran, 1948) as a measure of spatial autocorrelation, that is, the correlation between the values of basic units and their spatially related regions<sub>*j*</sub>. We define the spatial interrelations of the basic units on the basis of whether they share the same functional or administrative region. The results in Table 2 show the same pattern of the spatial autocorrelation measures

**TABLE 1** Comparison of the quality of various delineations

Delineation	Regions	Modularity	Commuters	(employment-)self-containment ratios <sup>a</sup>			
	No.	Q	%	Mean	SD	Min.	Max.
NU1 (NUTS 1, federal states)	16	0.789	9.5	86.6	6.6	71.8	95.7
NU2 (NUTS 2, former “Regierungsbezirke”)	38	0.819	14.7	84.7	5.9	65.2	93.7
NU3 (NUTS 3, districts)	402	0.613	38.1	58.9	13.6	20.5	86.7
EAD (employment agency districts)	156	0.718	27.3	71.5	10.8	45.6	91.6
SPR (spatial planning regions)	96	0.787	19.6	78.5	8.6	50.3	91.6
GRW (labour market regions of GRW)	258	0.733	25.5	69.3	10.3	32.7	91.2
RLM (regional labour markets)	141	0.785	19.9	75.9	9.4	42.0	91.3
LMR (labour market regions)	50	0.846	10.5	85.7	5.0	71.8	94.6
LLM (local labour market regions)	105	0.812	16.4	79.5	7.0	58.9	92.8

Notes: <sup>a</sup> Mean = arithmetic mean; SD = standard deviation.

Sources: Bundesagentur fuer Arbeit (Federal Employment Agency); authors own calculations.

**TABLE 2** Global spatial autocorrelation of indicators based on different delineations

Delineation	No. of Regions	Missing regions <sup>a</sup>	Unemployment rates		Employment rates		Income <i>per capita</i>	
			Morans I	SD	Morans I	SD	Morans I	SD
NU1 (NUTS 1, federal states)	16	2	0.566	0.001	0.303	0.001	0.247	0.001
NU2 (NUTS 2, former „Regierungsbezirke“)	38	2	0.581	0.002	0.331	0.002	0.285	0.002
NU3 (NUTS 3, districts)	402	107	0.685	0.006	0.545	0.006	0.363	0.006
EAD (employment agency districts)	154	12	0.644	0.004	0.468	0.004	0.342	0.004
SPR (spatial planning regions)	96	3	0.636	0.003	0.441	0.003	0.319	0.003
GRW (labour market regions of GRW)	258	10	0.675	0.005	0.520	0.005	0.332	0.005
RLM (regional labour markets)	141	0	0.665	0.004	0.478	0.004	0.307	0.004
LMR (labour market regions)	50	0	0.604	0.002	0.384	0.002	0.276	0.002
LLM (local labour market regions)	105	0	0.633	0.003	0.433	0.003	0.295	0.003

Note: <sup>a</sup>Some regions have to be excluded because of missing spatial neighbors within the respective delineation.

Sources: Bundesagentur fuer Arbeit (Federal Employment Agency); authors own calculations.

for the three indicators: spatial autocorrelation tends to be higher for functional regions than for administrative regions. However, spatial autocorrelation also tends to increase with the number of areal units, i.e. broader regions seem to be less able to capture homogeneous basic units, which is in line with previous research on MAUP effects (Cliff & Ord, 1981; Griffith et al., 2003). These results might reflect the scale or zoning effects of the MAUP (Lee et al., 2018). Although several studies have investigated the relationship between spatial autocorrelation and the MAUP, there is still uncertainty concerning the precise effects of the MAUP (Amrhein & Reynolds, 1996; Fotheringham, Densham, & Curtis, 1995; Fotheringham & Wong, 1991; Lee et al., 2018).

Table 3 presents the variation in the mean standard deviation of the economic indicators for the different regionalizations. For example, the mean standard deviation of the unemployment rates (measured at the level of 4,455 basic units) within administrative districts (NUTS 3) was 1.14 on average—the lowest value compared with all other delineations. However, there was at least one NUTS 3 region (district) with a very strong variation in unemployment rates, namely 3.88.<sup>4</sup>

The results show that the main reason for the positive relationship between spatial autocorrelation and the number of areal units, as reported in Table 2, is that the variance of the economic indicators within delineated regions decreases by the number of the total areal units (Fotheringham & Wong, 1991; Lee et al., 2018). Furthermore, regional delineations that capture commuting well, most notably LMR, LLM and NUTS 2—as measured by the indicators presented in Table 1—, do not cover areal units with very high variations (columns ‘max.’ in Table 3). In other words, within these regional units, strong commuting interrelations seem to be associated with a high level of homogenization. On average, however, NUTS 3 and the 258 GRW regions seem to combine more homogeneous basic units (columns ‘mean’ in Table 3). We find clear correlations between the number of delineated regions and the mean standard deviations of our indicators:  $-0.71$  ( $p$ -value: 0.03) for unemployment,  $-0.83$  (0.01) for employment rates, and  $-0.73$  (0.03) for income. Therefore, a sound analysis of homogeneity within aggregated regions should consider this interdependence.

In order to take a closer look at the spatial distribution of homogeneous areas throughout Germany, we additionally calculate Local Moran's I statistic, which measures the correlation between each single basic unit; and its spatial

<sup>4</sup>With respect to the NUTS 3 delineation, it is important to consider that city districts often form one single association of local authorities. In this case no variation within that region can be computed, resulting in 107 regions (districts) without standard deviation values (last column). This problem is far less prominent with other delineations.

**TABLE 3** Statistics on the variation of indicators within delineated regions

Delineation	Regions No.	SD of unemployment rates			SD of employment rates			SD of income per capita			SD missing		
		Mean	SD	Max.	Mean	SD	Max.	Mean	SD	Min.	Max.	N regions	
NU1 (NUTS 1, federal states)	16	1.90	0.74	3.11	5.54	1.53	3.04	9.45	3475.9	890.3	1636.3	4754.3	2
NU2 (NUTS 2, former „Regierungsbezirke“)	38	1.49	0.66	3.11	5.20	1.47	3.04	9.45	3663.6	873.9	1636.3	5424.6	2
NU3 (NUTS 3, districts)	402	1.14	0.65	3.88	4.25	1.88	1.09	12.63	3414.0	1281.1	710.1	8222.5	107
EAD (employment agency districts)	156	1.38	0.68	3.69	4.57	1.74	1.41	11.57	3509.2	1173.6	147.8	7747.6	12
SPR (spatial planning regions)	96	1.41	0.70	3.69	4.85	1.70	2.27	10.04	3576.4	990.0	1423.4	5992.0	3
GRW (labour market regions of GRW)	258	1.23	0.63	3.47	4.22	1.69	1.09	12.24	3394.3	1235.6	710.1	8222.5	10
RLM (regional labour markets)	141	1.34	0.69	3.88	4.74	1.91	2.27	12.24	3488.6	1084.6	1226.7	6614.9	0
LMR (labour market regions)	50	1.33	0.67	3.13	5.03	1.40	3.18	9.61	3580.8	838.7	2027.2	5542.4	0
LLM (local labour market regions)	105	1.29	0.61	3.13	4.46	1.53	1.92	9.61	3548.2	1036.6	1738.7	6452.1	0

Note: Mean = arithmetic mean; SD = standard deviation.

Sources: Bundesagentur fuer Arbeit (Federal Employment Agency); authors own calculations.



neighbours<sub>ij</sub>, that is, the spatial lag of each single basic unit<sub>i</sub> (Anselin, 1995). The calculations are based on inverse Euclidian distances to take into account the fact that regions close to each other are more strongly related than regions that are further apart; we only consider neighbouring regions which are up to 100 km apart. As an example we map the results for unemployment in Figure 3. The map reveals a high degree of positive spatial autocorrelation, especially in the eastern (high-high cluster) and in the southern part of Germany (low-low cluster). However, there also is a high degree of spatial clustering in Central-West. Overall, the results underpin our approach to take the structural differences between the four large German areas into account (see section on 'Methods'). Furthermore, the results demonstrate a substantial degree of negative spatial autocorrelation as well. This phenomenon is characteristic of the areas around the major cities in the East, Central-West and North-West regions of Germany (low-high cluster) or within large cities especially in the southern part of Germany (high-low cluster), where high unemployment in a city is accompanied by low values in the surrounding areas.



**FIGURE 3** Local spatial autocorrelation of unemployment

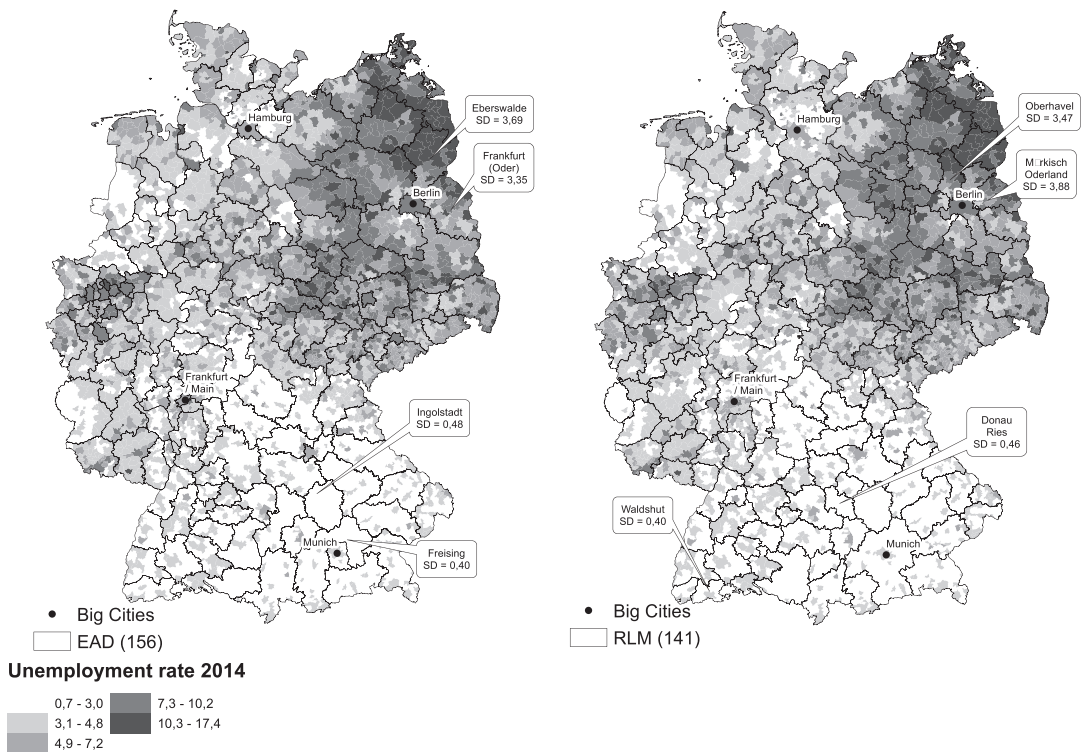
Source: BBSR, 2017, © GeoBasis-DE/BKG, 2014, authors' own calculations.



The two maps in Figure 4 illustrate how a delineation can capture homogeneity with regard to unemployment rates. Figure 4 shows these differences by comparing an administrative delineation (EAD) on the left-hand side with a functional delineation (RLM) on the right-hand side. We compare EAD and RLM because these two delineations comprise an almost equal number of regional units. This comparison enables us to focus on the zoning problem while keeping the scaling problem apart (see Section 3). At first glance, the two aggregations look quite similar. The main difference is that densely populated regions—for example, Hamburg, Berlin, Frankfurt (am Main) or Munich—are less aggregated in the EAD delineation. In both maps, light grey areas represent low unemployment rates, and dark grey areas represent high rates. The more similar the shades of grey within one region are, the more coherent the region is. In other words, the combination of basic units with similar shades of grey reflects a homogeneous regionalization.

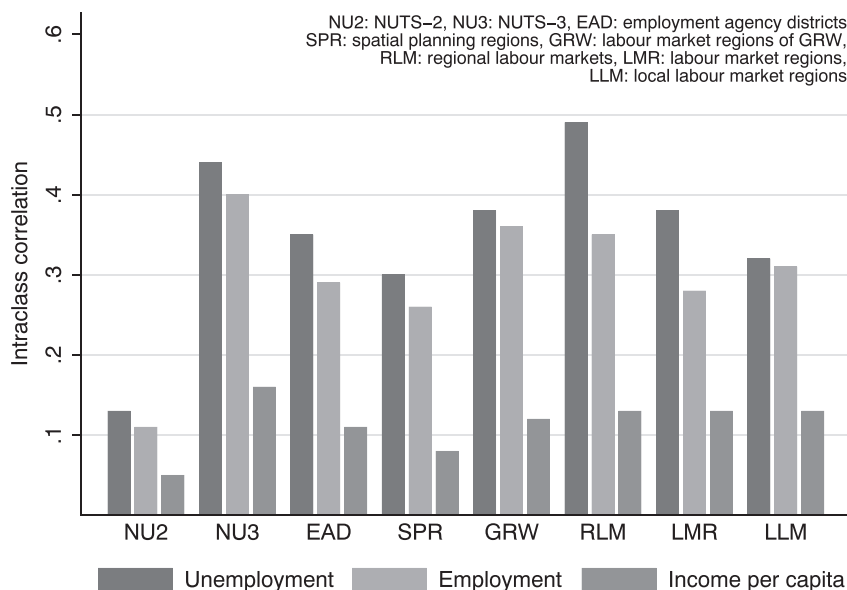
When investigating the shades of grey in the maps it becomes clear that some regions include basic units with low unemployment rates as well as units with high rates. This is especially true of the eastern part of Germany and the Rhine-Ruhr area in the west. For both the administrative delineation EAD and the functional delineation RLM, the highest variation in unemployment rates measured by SD within a region is in the northeast. In both delineations, Berlin's commuter belt, with its low unemployment rate, is combined with less advantaged regions further away, or—in the case of RLM—with Berlin itself.

The phenomenon of the city commuter belt (high unemployment in a city, low values in the surrounding areas) is characteristic of all functional regions. Delineations that keep the two region types apart—like most administrative delineations and especially NUTS 3—will therefore avoid this source of within-heterogeneity, but this will lead to substantial commuting relations being neglected. These descriptive findings provide first insights into spatial clustering captured by different regionalizations and the importance of the MAUP. The results reveal that spatial clustering does



**FIGURE 4** Unemployment rates at the basic unit level and selected delineations

Source: BBSR, 2017, © GeoBasis-DE/BKG, 2014.



**FIGURE 5** Spatial clustering of economic indicators, two-level linear mixed models

not always correspond to strong commuting. Delineations that capture commuting well, or functional delineations in general, therefore do not necessarily combine more homogeneous regions. However, for in-depth analyses of how different regionalizations perform, we compare within and between cluster variations systematically, and take into account characteristics of regional clusters as important controls.

## 5.2 | Multivariate analyses

We start our analyses with two-level random intercept models for the three economic indicators (unemployment, employment and income *per capita*), with administrative and functional regions comprising level 2. All the models take into account the size of the cluster to compare the different regionalizations. Also, the models consider general regional trends in labour market conditions in Germany in the four large areas East, South-West, Central West, and North-West (see previous section on data and methods). Due to the similarity between the four area indicators and the NUTS 1 delineation, we excluded NUTS 1 from the following analyses.<sup>5</sup> Figure 5 shows the ICCs for the different delineations. The ICCs reveal the degree of coherence of basic units within the different regions. Tables A1 in the Appendix present the detailed results of the models.

Regarding the three economic indicators, all the delineations show the same pattern of explanatory power: the estimates exhibit the largest regional variation for unemployment and the lowest for *per capita* income. The extent of overall variation, however, differs markedly between the different regional delineations. Even if the functional delineation RLM provides the best cluster solution and the administrative NUTS 2 delineation provides the worst, functional delineations do not yield better results overall than administrative delineations. The results are rather mixed for functional regions, and even the results for NUTS 3 regions and RLM do not differ substantially.

<sup>5</sup>As a robustness check, we conducted the analyses separately for the four broad regions to ensure that the relative difference between the ICCs based on different functional and administrative delineations is stable across the four German areas. The results do not differ from those we obtained based on all four regions.

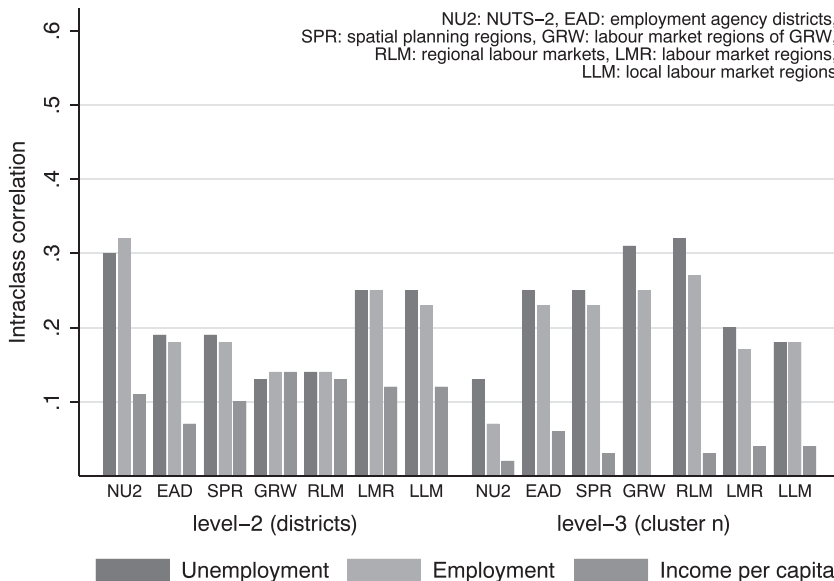


At first glance, the similar results obtained using the RLM functional delineation and the NUTS 3 administrative delineation seem surprising, but it might be explained by considering spatial scale and spatial zoning of the MAUP. On the one hand, NUTS 3 regions at a lower aggregation level may capture local spatial processes that are based on spatial proximity (spatial scale) well. On the other hand, the larger RLM regions may combine basic units that are interrelated due to spatial zoning and therefore form homogeneous areal units.

To examine the spatial interrelations more closely, we conduct three-level random intercept models with different regional clusters at level 3 and the lower aggregation level, NUTS 3 regions, at level 2 (Figure 6, see also tables A2a–c in the appendix). These models decompose the degree of homogeneity captured by the local NUTS 3 level and the more aggregated level of other administrative or functional delineations. Compared to Figure 5, the bars on the left-hand side of Figure 6 show that the explainable variance at NUTS 3 regional level decreases considerably when allowing for level 3 regional clustering (for unemployment, for instance, the ICC decreases from 0.44 in Figure 5 to 0.3 and lower in Figure 6 (left-hand side)). At the same time, the variance at level 3 decreases for the different regional clusters (right-hand side of Figure 6), e.g. for RLM by 17 percentage points.

The distribution of the explainable variance at level 2 and level 3 differs considerably for the regionalizations under study. Conspicuously, regions that capture commuting interrelations well (measured by modularity)—functional regions: LLM and LMR and administrative region: NU2—show high level-2 ICCs and low level-3 ICCs at the same time. In line with the findings presented in Figure 5, these regions comprise more heterogeneous basic units (nested in districts). In contrast, more disaggregated functional delineations (GRW and RLM), which are sensitive to local differences, can capture more level 3 variance at the expense of level 2 variance. The overall variation (proportion of level 2 plus level 3 variation) is quite similar for all delineations.

To sum up, economic functional regions do not generally reveal intra-regional homogeneity better than administrative regions (research question 1), although the functional delineations RLM and GRW perform best in capturing spatial clustering. Moreover, when comparing the two strongly aggregated functional and administrative regionalizations LMR and NUTS 2, the functional LMR delineation shows a much higher degree of homogenization.



**FIGURE 6** Spatial clustering of economic indicators, three-level linear mixed models





In answer to research question 2, delineations that capture commuting flows best (LMR and LLM) are rather heterogeneous regions. Moreover, in both the level 3 and level 2 models, modularity values correlate negatively with ICC values, even if these correlations are not statistically significant.<sup>6</sup>

Furthermore, concerning research question 3, our analyses emphasize that local spatial processes seem to lead to a homogenization of economic indicators, which especially areal units at a lower aggregation level, such as NUTS 3 or GRW, are able to capture. However, when looking at the results of the three-level model, despite local spatial clustering, there is a large degree of spatial interrelation that cannot be captured by any administrative delineation. The correlation between the number of delineated regions and the ICCs is statistically significant in the level 2 random intercept models for the unemployment and employment levels, and the level 3 random intercept models for employment.<sup>7</sup>

## 6 | CONCLUSION AND OUTLOOK

This paper aimed to evaluate whether economic functional regions are more homogeneous than administrative regions and, therefore, better able to capture spatial clustering of economic characteristics at the level of municipalities resulting from spatial interrelations. This would indeed be a point in favour of functional regions because it could enable political actors to apply a rather simple set of policies within functional regions. In order to shed light on the coherence of functional regions, we draw on level 2 as well as on level 3 hierarchical linear models (HLM) and compare intraclass correlation coefficients (ICC), which enable us to reveal the degree of homogenization at different levels of aggregation. This is a new approach to evaluate different regionalizations. It helps us to understand how the characteristics of different (functional) delineations are related to processes of homogenization.

The argument as to why economic functional regions could be more homogeneous than administrative regions is that they capture economic interactions (e.g., mobility patterns) which are seen to be responsible for homogenization processes. However, our descriptive analyses reveal that German functional delineations do not always capture mobility flows of the labour force better than administrative ones. Economic functional delineations are based on commuting flows and often connect cities and their hinterland. As the cities and the hinterland are usually very heterogeneous concerning unemployment, employment and income levels, functional regions are consequently characterized by a noticeable degree of heterogeneity.

With these findings in mind, the results of our analyses are not surprising. First, we find that economic functional regions do not always reveal intra-regional homogeneity better than administrative regions. This holds especially for functional regions that capture mobility patterns very well. They exhibit lower ICCs than administrative regions such as administrative districts or employment agency districts. Consequently, regarding our second research question we find that delineations with high modularity values do not form more homogeneous regional units than other delineations. In fact the opposite is true, although this finding is not statistically significant. Finally, concerning our third research question, it appears that more differentiated delineations are better at forming homogeneous regions.

In general, our analyses reveal a complex relationship between (functional) delineations and the aim to delineate homogeneous regions. For Germany, the spatial distribution of employment and income is not necessarily shaped by commuting patterns. In some cases, strong commuting flows connect very heterogeneous regions, which include

<sup>6</sup>The Pearson correlation coefficient between modularity Q and ICC (Figure 2, Table A1) is  $-0.42$  (p-value: 0.30) for unemployment,  $-0.61$  (0.11) for employment, and  $-0.49$  (0.21) for income. Correlations between modularity Q and ICC level 3 (Figure 3, Table A2):  $-0.63$  (0.13) for unemployment,  $-0.61$  (0.15) for employment, and  $0.02$  (0.97) for income.

<sup>7</sup>The Pearson correlation coefficients between the number of regions and ICC (Figure 2, Table A1):  $0.55$  (p-value: 0.16) for unemployment,  $0.76$  (0.03) for employment, and  $-0.65$  (0.08) for income. The correlations between the number of regions and ICC level 3 (Figure 3, Table A2):  $0.79$  (0.04) for unemployment,  $0.72$  (0.07) for employment, and  $-0.37$  (0.41) for income.



cities and their commuter belts. This is in line with some empirical findings that show how mobility processes can even reinforce regional inequality (Granato et al., 2015; Kanbur & Rapoport, 2005; Südekum, 2004). Therefore, methods that capture commuting patterns well are not suitable for delineating homogeneous regions, at least for Germany. There are forces at work that contradict the neoclassical predictions on the levelling effects of mobility. For instance, Windzio (2004) argues that high regional unemployment discourages mobility, resulting in an “unemployment trap.”

Furthermore, even if spatial interaction, like commuting, may lead to homogenization, there might be other simultaneous processes at work as well, such as agglomeration, which lead to differentiation, for example, due to different levels of land prices. Also, considering regional specialization and commuting or the migration of specialized workers, for instance, homogenization may only concern specific indicators but neglect others. Further research on spatial mobility decision-making will be necessary, with regard to both individual conditions (e.g., skill levels, socio-economic resources) and structural conditions (e.g., accessibility, unemployment, employment structure). It is difficult to generalize these findings. While we expect the mechanisms of homogenization (via commuting and mobility) and differentiation (via economic specialization) to be universal, particularities of the spatial organization in other countries might lead to a different balance of homogenization and differentiation processes. This is certainly an interesting challenge for further research.

With regard to the MAUP, we are unable to answer the question as to whether economic functional regions deal with it better than administrative regions, or to put it differently, what kind of regional delineations deal best with the MAUP. However, our analyses reveal that both dimensions of the MAUP—spatial scale and spatial zoning—should be taken into consideration. Concerning spatial zoning, we found strong evidence of the advantages of functional regions over administrative regions: above all the 141 regional labour markets (RLM) used by Kosfeld and Werner (2012). As regards spatial scale, we found relevant spatial clustering of economic indicators depicted by the less aggregated NUTS 3 level (which in our case is the best delineation to take this kind of clustering into account, because the boundaries of NUTS 3 regions correspond with all other regional clusters at a higher aggregation level).

To conclude, our results for Germany suggest that economic functional delineations are not able to capture both commuting interrelations and spatial clustering or homogeneity very well. This is an argument in favour of not relying solely on measures related to self-containment, such as modularity. Homogeneity-related measures, or measures of interaction density (Casado-Díaz, Martínez-Bernabéu, & Flórez-Revuelta, 2017), may be appropriate indices for delineating well differentiated functional areas, which are especially capable of capturing spatial clustering at a lower aggregation level.

## ORCID

Alexandra Wicht  <https://orcid.org/0000-0002-2183-8860>

## REFERENCES

- Akerlof, G. A. (1997). Social distance and social decisions. *Econometrica*, 65, 1005–1027.
- Amrhein, C. G., & Reynolds, H. (1996). Using spatial statistics to assess aggregation effects. *Geographical Systems*, 3, 143–158.
- Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis*, 27, 93–115.
- Anselin, L. (2003). Spatial externalities, spatial multipliers, and spatial econometrics. *International Regional Science Review*, 26, 153–166.
- Arbia, G. (2001). Modelling the geography of economic activities on a continuous space. *Papers in Regional Science*, 80, 411–424.
- BBSR (2017). *Indikatoren und Karten zur Raum- und Stadtentwicklung*. Bonn: INKAR.
- Berry, C. R., & Glaeser, E. L. (2005). The divergence of human capital levels across cities. *Papers in Regional Science*, 84, 407–444.
- Brunsdon, C., & Comber, L. (2015). *An introduction to R for spatial analysis and mapping*. London: Sage.



- Casado-Díaz, J. M., Martínez-Bernabéu, L., & Flórez-Revuelta, F. (2017). Automatic parameter tuning for functional regionalization methods. *Papers in Regional Science*, 96, 859–879.
- Cliff, A. D., & Ord, J. K. (1981). *Spatial processes: Models and applications*. London: Pion.
- Combes, P.-P., Mayer, T., & Thisse, J.-F. (2008). *Economic geography. The integration of regions and nations*. Princeton, NJ: Princeton University Press.
- Conley, T. G., & Topa, G. (2002). Socio-economic distance and spatial patterns in unemployment. *Journal of Applied Econometrics*, 17, 303–327.
- Coombes, M. G., Green, A. E., & Openshaw, S. (1986). An efficient algorithm to generate official statistical reporting areas: The case of the 1984 travel-to-work areas revision in Britain. *Journal of Operational Research Society*, 37, 943–953.
- Cörvers, F., Hensen, M., & Bongaerts, D. (2009). Delimitation and coherence of functional and administrative regions. *Regional Studies*, 43, 19–31.
- Cushing, B., & Poot, J. (2004). Crossing boundaries and borders: Regional science advances in migration modelling. *Papers in Regional Science*, 83, 317–338.
- Elhorst, P. J. (2003). The mystery of regional unemployment differentials: Theoretical and empirical explanations. *Journal of Economic Surveys*, 17, 709–748.
- Fotheringham, A. S., Densham, P. J., & Curtis, A. (1995). The zone definition problem in location-allocation modeling. *Geographical Analysis*, 27, 60–77.
- Fotheringham, A. S., & Wong, D. W. S. (1991). The modifiable areal unit problem in multivariate statistical analysis. *Environment and Planning A*, 23, 1025–1044.
- Frick, J. R., & Göbel, J. (2008). Regional income stratification in unified Germany using a Gini decomposition approach. *Regional Studies*, 42, 555–577.
- Fujita, M., & Mori, T. (2005). Frontiers of the new economic geography. *Papers in Regional Science*, 84, 377–405.
- Goldstein, H. G. (2011). *Multilevel statistical models*. Chichester: John Wiley & Sons.
- Granato, N., Haas, A., Hamann, S., & Niebuhr, A. (2015). The impact of skill-specific migration on regional unemployment disparities in Germany. *Journal of Regional Science*, 55, 513–539.
- Griffith, D. A., Wong, D. W. S., & Whitfield, T. (2003). Exploring relationships between the global and regional measures of spatial autocorrelation. *Journal of Regional Science*, 43, 683–710.
- Halleck Vega, S., & Elhorst, J. P. (2016). A regional unemployment model simultaneously accounting for serial dynamics, spatial dependence and common factors. *Regional Science and Urban Economics*, 60, 85–95.
- Hensen, M. M., & Cörvers, F. (2003). *The regionalization of labour markets by modelling commuting behaviour*. (paper) onbekend, Researchcentrum Onderwijs & Arbeidsmarkt.
- IAB (2016). Employment history (Beschäftigtenhistorik, BeH). V10.01.00. Nuremberg
- Kanbur, R., & Rapoport, H. (2005). Migration selectivity and the evolution of spatial inequality. *Journal of Economic Geography*, 5, 43–57.
- Korpi, M., & Clark, W. A. V. (2019). Migration and occupational careers: The static and dynamic urban wage premium by education and city size. *Papers in Regional Science*, 98, 555–574.
- Kosfeld, R., & Werner, A. (2012). Deutsche Arbeitsmarktregionen: Neuabgrenzung nach den Kreisgebietsreformen 2007–2011. *Raumforschung Und Raumordnung*, 70, 49–64.
- Kropp, P., & Schwengler, B. (2011). Abgrenzung von Arbeitsmarktregionen: Ein Methodenvorschlag. *Raumforschung Und Raumordnung*, 69, 45–62.
- Kropp, P., & Schwengler, B. (2016). Three-step method for delineating functional labour market regions. *Regional Studies*, 50, 429–445.
- Krugman, P. (1991). *Geography and trade*. Cambridge, MA: MIT Press.
- Lee, S.-I., Lee, M., Chun, Y., & Griffith, D. A. (2018). Uncertainty in the effects of the modifiable areal unit problem under different levels of spatial autocorrelation: A simulation study. *International Journal of Geographical Information Science*, 33, 1135–1154.
- Logan, J. R. (2012). Making a place for space. Spatial Thinking in Social Science. *Annual Review of Sociology*, 38, 149–176.
- Moran, P. A. P. (1948). The interpretation of statistical maps. *Journal of the Royal Statistical Society. Series B*, 10, 243–251.
- Newman, M. E. J., & Girvan, M. (2004). Finding and evaluating community structure in networks. *Physical Review*, E, 69, 1–15.
- Niebuhr, A., Granato, N., Haas, A., & Hamann, S. (2012). Does labour mobility reduce disparities between regional labour markets in Germany? *Regional Studies*, 46, 841–858.



- OECD (2016). *OECD Employment Outlook, 2016*. Paris: OECD.
- Openshaw, S. (1984). *The modifiable areal unit problem. (Concepts and Techniques in Modern Geography 38)*. Norwich: Geo Books.
- Openshaw, S., & Taylor, P. J. (1979). A million or so correlation coefficients: Three experiments on the modifiable areal unit problem. In N. Wrigley (Ed.), *Statistical Applications in the Spatial Science* (pp. 127–144). London: Pion.
- Patacchini, E., & Zenou, Y. (2007). Spatial dependence in local unemployment rates. *Journal of Economic Geography*, 7, 169–191.
- Rabe-Hesketh, S., & Skrondal, A. (2012). Multilevel and longitudinal modeling using Stata. In *Volume I: Continuous responses*. College Station, TX: Stata Press.
- Rios, V. (2017). What drives unemployment disparities in European regions? A dynamic spatial panel approach. *Regional Studies*, 51, 1599–1611.
- Smart, M. W. (1974). Labour market areas: Uses and definition. *Progress in Planning*, 2, 239–353.
- Statistische Ämter des Bundes und der Länder (Statistical offices of the Federation and the Länder). (2018). Population aged 15–65 at the regional level of Associations of Local Authorities, Germany. Düsseldorf.
- Südekum, J. (2004). Selective migration, union wage setting and unemployment disparities in West-Germany. *International Economic Journal*, 18, 33–48.
- Südekum, J. (2005). Increasing returns and spatial unemployment disparities. *Papers in Regional Science*, 84, 159–181.
- Tobler, W. R. (1970). A computer Mmovie simulating urban growth in the Detroit region. *Economic Geography*, 46, 234–240.
- Van der Laan, L., & Schalke, R. (2001). Reality versus policy: The delineation and testing of local labour market and spatial policy areas. *European Planning Studies*, 9, 201–221.
- Wicht, A. (2017). From place to space: Regional contexts in the sociology of education. In A. Million, A. J. Heinrich, & T. Coelen (Eds.), *Education, space, and urban planning: Education as a component of the city* (pp. 299–307). Luxemburg: Springer International.
- Windzio, M. (2004). Kann der regionale Kontext zur "Arbeitslosenfalle" werden? Der Einfluss der Arbeitslosigkeit auf die Mobilität zwischen regionalen Arbeitsmärkten in Westdeutschland. *Kölner Zeitschrift für Soziologie Und Sozialpsychologie*, 56, 256–278.
- Wixforth, J., & Soyka, A. (2005). Abgrenzung der Stadtregionen Hamburg und Berlin-Potsdam auf basis von Pendlerverflechtungen. *Beiträge Zur sozialökonomischen Stadtforschung*, 1, 1–13.
- Wong, D. (2009). The modifiable areal unit problem. In A. S. Fotheringham, & P. A. Rogerson (Eds.), *The Sage handbook of spatial analysis*. London: Sage.

**How to cite this article:** Wicht A, Kropp P, Schwengler B. Are functional regions more homogeneous than administrative regions? A test using hierarchical linear models. *Pap Reg Sci*. 2019;99:135–164. <https://doi.org/10.1111/pirs.12471>



## APPENDIX A

TABLE A1 Spatial clustering of economic indicators, two-level linear mixed models

a: unemployment	NU2	NU2	NU3	EAD	EAD	SPR	SPR
<i>Level 2 control variables</i>							
Cluster size	-0.01 [0.002]	-0.07 [0.009]	-0.03 [0.006]			-0.02 [0.005]	
Population of working age	0.00 [0.000]	0.00 [0.000]	0.00 [0.000]			0.00 [0.000]	
<i>Level 1 control variables</i>							
Area, ref. East							
North west	-2.64 [0.363]	-2.65 [0.225]	-2.89 [0.296]			-3.04 [0.317]	
Central west	-3.46 [0.371]	-2.85 [0.213]	-2.61 [0.278]			-3.14	
South west	-4.31 [0.288]	-4.28 [0.179]	-4.19 [0.258]			-4.63 [0.278]	
Constant	4.57 [0.308]	4.72 [0.111]	8.14 [0.200]	4.82 [0.174]	8.17 [0.282]	4.64 [0.216]	7.97 [0.289]
No. of groups	38	402	402	154	154	96	96
Level 2 variance	3.48	4.51	1.35	4.47	1.09	4.39	0.89
Level 1 variance	2.44	1.73	1.74	2.04	2.05	2.11	2.11
ICC	0.59	0.72	0.44	0.69	0.35	0.67	0.30
	<b>GRW</b>	<b>GRW</b>	<b>RLM</b>	<b>LMR</b>	<b>LMR</b>	<b>LLM</b>	<b>LLM</b>
<i>Level 2 control variables</i>							
Cluster size	-0.03 [0.008]	-0.02 [0.007]	0.00 [0.003]			-0.01 [0.004]	
Population of working age	0.00 [0.000]	0.00 [0.000]	0.00 [0.000]			0.00 [0.000]	
<i>Level 1 control variables</i>							
Area, ref. East							
North west	-2.7 [0.242]	-0.95 [0.242]	-1.88 [0.206]			-1.53 [0.257]	
Central west	-2.89 [0.236]	-1.79 [0.301]	-1.80 [0.265]			-2.18 [0.254]	
South west	-4.38 [0.194]	-2.52 [0.211]	-2.45 [0.266]			-2.99 [0.231]	
Constant	4.48 [0.130]	4.63 [0.185]	6.09 [0.287]	4.38 [0.283]	6.09 [0.287]	4.26 [0.183]	6.34 [0.232]
No. of groups	258	141	50	50	50	105	105

(Continues)



**TABLE A1** (Continued)

a: unemployment	NU2	NU2	NU3	NU3	EAD	SPR	SPR
Level 2 variance	4.14	1.16	1.89	4.74	3.96	3.42	1.04
Level 1 variance	1.87	1.87	1.95	1.94	2.31	2.14	2.16
ICC	0.69	0.38	0.49	0.71	0.63	0.61	0.32
b: employment	NU2	NU2	NU3	NU3	EAD	SPR	SPR
<i>Level 2 control variables</i>							
Cluster size		0.01 [0.008]	0.05 [0.030]		0.03 [0.018]		0.01 [0.016]
Population of working age		0.00 [0.000]	0.00 [0.000]		0.00 [0.000]		0.00 [0.000]
<i>Level 1 control variables</i>							
Area, ref. East							
North west		5.08 [1.247]	4.49 [0.762]		4.85 [0.947]		4.84 [1.063]
Central west		4.88 [1.279]	3.67 [0.726]		3.94 [0.893]		3.73 [1.144]
South west		8.23 [0.988]	8.56 [0.607]		8.12 [0.825]		9.05 [0.931]
Constant	54.45 [0.651]	47.68 [1.223]	54.63 [0.280]	48.68 [0.683]	54.27 [0.405]	54.45 [0.496]	48.95 [0.967]
No. of groups	38	38	402	402	154	96	96
Level 2 variance	14.96	4.2	26.16	15.12	22.96	22.44	9.81
Level 1 variance	33.09	33.08	22.72	22.70	26.42	27.65	27.64
ICC	0.31	0.11	0.54	0.40	0.46	0.45	0.26
	GRW	GRW	RLM	RLM	LMR	LLM	LLM
<i>Level 2 control variables</i>							
Cluster size		0.05 [0.028]	0.01 [0.018]		0.01 [0.007]		0.03 [0.012]
Population of working age		0.00 [0.000]	0.00 [0.000]		0.00 [0.000]		0.00 [0.000]
<i>Level 1 control variables</i>							
Area, ref. East							
North west		5.06 [0.834]	1.21 [0.780]		2.24 [0.725]		3.04 [0.908]

(Continues)



TABLE A1 (Continued)

b: employment	NU2	NU2	NU3	NU3	EAD	EAD	SPR	SPR
Central west		4.46 [0.817]	2.50 [0.902]		5.70 [0.893]		6.24 [0.896]	
South west		8.53 [0.670]	6.56 [0.666]		5.70 [0.875]		7.07 [0.812]	
Constant	54.45 [0.325]	48.35 [0.675]	54.25 [0.432]	50.14 [0.698]	54.35 [0.646]	50.00 [0.878]	54.79 [0.472]	49.34 [0.812]
No. of groups	258	258	141	141	50	50	105	105
Level 2 variance	25	13.69	25.08	14.04	20.17	11.73	22.26	12.42
Level 1 variance	23.92	23.91	25.78	25.69	30.45	30.33	28.16	28.10
ICC	0.51	0.36	0.49	0.35	0.40	0.28	0.44	0.31
c: income per capita	NU2	NU2	NU3	NU3	EAD	EAD	SPR	SPR
Level 2 control variables								
Cluster size		-16.43 [3.679]	-151.80 [15.184]		-77.79 [8.097]		-46.39 [6.405]	
Population of working age		0.19 [0.028]	1.01 [0.105]		0.59 [0.086]		0.34 [0.042]	
Level 1 control variables								
Area, ref. East								
North west		2007.20 [604.692]	1721.61 [374.543]		1697.89 [426.245]		1920.03 [442.962]	
Central west		2925.94 [628.263]	3571.27 [365.784]		3915.68 [415.145]		3399.00 [480.775]	
South west		4728.34 [472.401]	5100.28 [290.577]		5747.53 [368.068]		5423.58 [376.210]	
Constant	25379.01 [421.519]	21712.88 [593.591]	25758.72 [168.082]	23144.59 [347.849]	25659.92 [261.924]	22721.23 [414.768]	25235.74 [292.758]	22492.50 [398.682]
No. of groups	38	38	402	402	154	154	96	96
Level 2 variance	6240482.55	890180.36	8482606.18	2634801.54	9381851.46	1747833.24	7642444.37	1355556.35
Level 1 variance	15985455.78	15991088.51	14052662.71	13990951.03	14689511.52	14674062.14	15240497.48	15248437.16
ICC	0.28	0.05	0.38	0.16	0.39	0.11	0.33	0.08
GRW	GRW	RLM	RLM	RLM	LMR	LMR	LLM	LLM
Level 2 control variables								
Cluster size		-69.79 [12.589]	-25.35 [8.001]		-7.82 [3.417]		-22.80 [5.770]	

(Continues)



TABLE A1 (Continued)

c: income per capita	NU2	NU2	NU3	NU3	EAD	EAD	SPR	SPR
Population of working age	0.48 [0.060]		0.21 [0.044]		0.08 [0.027]		0.15 [0.037]	
<i>Level 1 control variables</i>								
<i>Area, ref. East</i>								
North west	1901.55 [382.171]		1975.85 [428.712]		2230.55 [473.786]		2182.36 [509.899]	
Central west	4145.84 [380.397]		4357.52 [443.759]		3695.25 [532.981]		4070.53 [488.083]	
South west	4646.94 [295.910]		4817.86 [349.335]		4615.55 [492.690]		5004.38 [424.470]	
Constant	25155.46 [176.283]	22270.74 [306.791]	24983.22 [239.296]	21897.13 [332.885]	25054.07 [376.205]	21864.78 [452.988]	25415.74 [267.024]	22172.99 [411.594]
No. of groups	258	258	141	141	50	50	105	105
Level 2 variance	6705952.11	2039828.49	7321433.12	2302517.61	6698668.10	2392387.78	6863435.90	2400134.50
Level 1 variance	15001195.00	15010781.77	15548681.02	15500442.30	16176549.99	16111822.69	15771926.50	15750598.92
ICC	0.31	0.12	0.32	0.13	0.29	0.13	0.3	0.13

Notes: N (associations of local authorities) 4,455; S.E. in brackets; datasource: BBSR 2016/BeH 2016.

NU2: NUTS-2, NU3: NUTS-3, SPR: spatial planning regions, GRW: labour market regions of GRW, EAD: employment agency districts, RLM: regional labour markets, LMR: labour market regions, LLM: local labour market regions




**TABLE A2** Spatial clustering of economic indicators, three-level linear mixed models

a: Unemployment	NU2	NU2	EAD	EAD	SPR	SPR	GRW	GRW
<i>Level 3 control variables</i>								
Cluster size		-0.01 [0.003]	-0.01 [0.006]		-0.00 [0.005]		0.01 [0.008]	
Population of working age		0.00 [0.000]	0.00 [0.000]		0.00 [0.000]		0.00 [0.000]	
<i>Level 2 control variables</i>								
Cluster size		-0.08 [0.008]	-0.08 [0.008]		-0.07 [0.008]		-0.08 [0.008]	
Population of working age		0.00 [0.000]	0.00 [0.000]		0.00 [0.000]		0.00 [0.000]	
<i>Level 1 control variables</i>								
Area, ref. east								
North west		-3.00 [0.423]	-2.91 [0.296]		-3.01 [0.336]		-2.73 [0.255]	
Central west		-3.73 [0.445]	-2.84 [0.283]		-3.17 [0.361]		-2.96 [0.248]	
South west		-4.40 [0.336]	-4.16 [0.257]		-4.61 [0.292]		-4.34 [0.205]	
Constant	4.78 [0.305]	8.89 [0.456]	4.94 [0.171]	9.02 [0.303]	4.8 [0.214]	8.57 [0.323]	4.64 [0.129]	8.09 [0.228]
No. of groups	38	38	154	154	96	96	258	258
Level 3 variance	3.28	0.38	3.85	0.76	4.06	0.79	3.10	0.96
Level 2 variance	1.08	0.90	0.84	0.60	0.75	0.60	1.27	0.40
Level 1 variance	1.75	1.73	1.75	1.74	1.76	1.74	1.74	1.74
ICC (cluster i)	0.54	0.13	0.60	0.25	0.62	0.25	0.51	0.31
ICC (districts)	0.17	0.30	0.13	0.19	0.11	0.19	0.20	0.13

(Continues)



**TABLE A2** (Continued)

a: Unemployment	NU2		EAD		SPR		GRW	
	RLM	RLM	LMR	LMR	LLM	LLM	GRW	GRW
<i>Level 3 control variables</i>								
Cluster size		-0.00 [0.006]		-0.00 [0.002]		-0.01 [0.003]		
Population of working age		0.00 [0.000]		0.00 [0.000]		0.00 [0.000]		
<i>Level 2 control variables</i>								
Cluster size		-0.08 [0.008]		-0.07 [0.008]		-0.07 [0.008]		
Population of working age		0.00 [0.000]		0.00 [0.000]		0.00 [0.000]		
<i>Level 1 control variables</i>								
Area, ref. east								
North west		-2.27 [0.287]		-2.66 [0.337]		-2.56 [0.307]		
Central west		-2.90 [0.295]		-3.39 [0.348]		-3.17 [0.293]		
South west		-3.89 [0.243]		-3.69 [0.309]		-3.98 [0.251]		
Constant	4.74 [0.184]	8.17 [0.247]	4.58 [0.278]	8.00 [0.301]	4.47 [0.186]	8.11 [0.270]		
No. of groups	141	141	50	50	105	105		
Level 3 variance	4.42	1.05	3.54	0.62	3.16	0.54		
Level 2 variance	0.47	0.46	0.94	0.80	0.86	0.77		
Level 1 variance	1.77	1.74	1.75	1.73	1.75	1.73		

(Continues)



TABLE A2 (Continued)

a: Unemployment		NU2	NU2	EAD	EAD	SPR	SPR	GRW	GRW
ICC (cluster 1)		0.66	0.32	0.57	0.20	0.55	0.18		
ICC (districts)		0.07	0.14	0.15	0.25	0.14	0.25		
b: Employment		NU2	NU2	EAD	EAD	SPR	SPR	GRW	GRW
<i>Level 3 control variables</i>									
Cluster size			0.02 [0.008]		0.02 [0.021]		0.00 [0.017]		0.04 [0.032]
Population of working age			-0.00 [0.000]		0.00 [0.000]		-0.00 [0.000]		-0.00 [0.000]
<i>Level 2 control variables</i>									
Cluster size			0.06 [0.030]		0.08 [0.029]		0.07 [0.028]		0.05 [0.029]
Population of working age			0.00 [0.000]		0.00 [0.000]		0.00 [0.000]		0.00 [0.000]
<i>Level 1 control variables</i>									
Area, ref. east									
North west			5.38 [1.247]		5.11 [0.999]		4.88 [1.126]		5.03 [0.846]
Central west			5.54 [1.325]		4.29 [0.956]		4.08 [1.208]		4.47 [0.826]
South west			8.42 [0.984]		8.28 [0.867]		9.05 [0.975]		8.40 [0.678]
Constant		54.25 [0.639]	45.81 [1.374]	54.20 [0.401]	46.87 [1.027]	54.32 [0.495]	47.80 [1.085]	54.37 [0.324]	47.72 [0.764]
No. of groups		38	38	154	154	96	96	258	258
Level 3 variance		12.98	2.73	18.96	8.57	20.15	8.64	19.98	9.52
Level 2 variance		12.35	11.97	7.32	6.64	7.24	6.84	5.80	5.33

(Continues)



**TABLE A2** (Continued)

<b>b: employment</b>	<b>NU2</b>	<b>NU2</b>	<b>EAD</b>	<b>EAD</b>	<b>EAD</b>	<b>SPR</b>	<b>SPR</b>	<b>SPR</b>	<b>GRW</b>	<b>GRW</b>
Level 1 variance	22.71	22.69	22.68	22.67	22.68	22.65	22.67	22.65	22.67	22.65
ICC (cluster i)	0.27	0.07	0.39	0.23	0.40	0.23	0.41	0.23	0.41	0.25
ICC (districts)	0.25	0.32	0.14	0.18	0.14	0.18	0.11	0.18	0.11	0.14
	<b>RLM</b>	<b>RLM</b>	<b>LMR</b>	<b>LMR</b>	<b>LLM</b>	<b>LLM</b>		<b>LLM</b>		
<i>Level 3 control variables</i>										
Cluster size		-0.01 [0.018]		0.01 [0.006]				0.02 [0.011]		
Population of working age		0.00 [0.000]		-0.00 [0.000]				-0.00 [0.000]		
<i>Level 2 control variables</i>										
Cluster size		0.09 [0.026]		0.07 [0.028]				0.06 [0.028]		
Population of working age		0.00 [0.000]		0.00 [0.000]				0.00 [0.000]		
<i>Level 1 control variables</i>										
Area, ref. east										
North west		3.20 [0.944]		4.17 [1.146]				4.85 [1.069]		
Central west		3.48 [0.966]		6.22 [1.179]				5.88 [1.023]		
South west		7.64 [0.796]		6.70 [1.040]				8.17 [0.876]		
Constant	54.14 [0.429]	48.16 [0.813]	54.13 [0.624]	47.84 [1.018]	54.57 [0.468]	47.38 [0.942]				
No. of groups	141	141	50	50	105	105		105		
Level 3 variance	21.82	10.51	16.22	6.62	17.92	6.86				

(Continues)



TABLE A2 (Continued)

	NIU2	NIU2	EAD	EAD	SPR	SPR	GRW	GRW
<b>b: employment</b>								
Level 2 variance	5.62	5.26	9.82	9.58	8.73	8.59		
Level 1 variance	22.66	22.65	22.70	22.67	22.68	22.67		
ICC (cluster i)	0.44	0.27	0.33	0.17	0.36	0.18		
ICC (districts)	0.11	0.14	0.20	0.25	0.17	0.23		
<b>c: Income per capita</b>								
<i>Level 3 control variables</i>								
Cluster size		-8.96 [3.003]		-52.97 [8.898]		-24.19 [6.353]		14.10 [12.242]
Population of working age		0.13 [0.024]		0.34 [0.108]		0.23 [0.042]		0.08 [0.062]
<i>Level 2 control variables</i>								
Cluster size		-122.47 [15.110]		-93.90 [15.231]		-109.43 [15.838]		-154.64 [16.809]
Population of working age		0.65 [0.115]		0.47 [0.139]		0.57 [0.119]		0.84 [0.128]
<i>Level 1 control variables</i>								
Area, ref. east								
North west		1340.26 [493.212]		1467.45 [415.022]		1597.34 [411.866]		1646.50 [367.229]
Central west		2475.48 [531.088]		3399.95 [410.999]		2927.55 [435.541]		3628.28 [360.539]
South west		4775.07 [379.619]		5665.21 [354.178]		5176.28 [339.976]		4799.50 [282.957]

(Continues)



**TABLE A2** (Continued)

c: income per capita	NIU2	NIU2	EAD	EAD	SPR	SPR	SPR	GRW	GRW
Constant	25565.85 [421.444]	22844.62 [559.019]	25720.02 [258.062]	23675.30 [453.786]	25365.94 [289.780]	23163.21 [409.220]	25401.29 [179.391]	22933.66 [346.068]	25401.29 [179.391]
No. of groups	38	38	154	154	96	96	258	258	258
Level 3 variance	5982922.82	308906.18	8537162.73	1034441.22	6969911.92	559276.47	3969539.54	0.10	0.10
Level 2 variance	2066518.83	1852518.35	1037937.99	1066333.11	15586693.39	1556025.70	3765203.84	2306555.66	3765203.84
Level 1 variance	14124852.34	13970631.86	14181215.83	14032152.62	14143474.86	13986374.33	14098811.34	13993502.35	14098811.34
ICC (cluster I)	0.27	0.02	0.36	0.06	0.31	0.03	0.18	0.00	0.18
ICC (districts)	0.09	0.11	0.04	0.07	0.06	0.10	0.17	0.14	0.17
	<b>RLM</b>	<b>RLM</b>	<b>LMR</b>	<b>LMR</b>	<b>LLM</b>	<b>LLM</b>	<b>LLM</b>		
<i>Level 3 control variables</i>									
Cluster size		-0.65 [6.498]		-1.89 [2.255]					-5.42 [4.037]
Population of working age		0.07 [0.036]		0.03 [0.018]					0.04 [0.026]
<i>Level 2 control variables</i>									
Cluster size		-145.56 [16.359]		-133.17 [15.404]					-138.63 [15.695]
Population of working age		0.87 [0.113]		0.86 [0.107]					0.89 [0.109]
<i>Level 1 control variables</i>									
Area, ref. east									
North west		1601.39 [399.689]		1786.59 [504.514]					1665.57 [454.566]
Central west		3529.11 [391.738]		3263.71 [509.678]					3419.34 [441.626]
South west		4978.06 [320.554]		4825.22 [431.565]					5040.79 [362.484]

(Continues)



TABLE A2 (Continued)

c: income per capita	NU2	NU2	EAD	EAD	SPR	SPR	GRW	GRW
Constant	25222.54 [234.470]	22946.84 [363.386]	25235.16 [370.231]	22909.58 [449.606]	25551.83 [261.638]	23179.10 [423.335]		
No. of groups	141	141	50	50	105	105		
Level 3 variance	5686159.90	417201.18	5818409.89	739634.41	5430081.72	606574.90		
Level 2 variance	2615777.52	2113468.84	2423976.46	1946164.27	2497995.83	2030633.77		
Level 1 variance	14142502.05	13988850.15	14149829.05	13987234.39	14143809.29	13988875.28		
ICC (cluster i)	0.25	0.03	0.26	0.04	0.25	0.04		
ICC (districts)	0.11	0.13	0.10	0.12	0.11	0.12		

Notes: N (associations of local authorities) 4,455; N (districts) 402; S.E. in brackets; datasource: BBSR 2016/BeH 2016

Legend: NU2: NUTS-2, NU3: NUTS-3, SPR: spatial planning regions, GRW: labour market regions of GRW, EAD: employment agency districts, RLM: regional labour markets, LMR: labour market regions, LLM: local labour market regions



**Resumen.** El artículo investiga si las regiones económicas funcionales capturan la agrupación espacial de los indicadores económicos básicos mejor que las regiones administrativas. Para ello utiliza modelos lineales jerárquicos, con el fin de medir el grado de homogeneización de las diferentes delimitaciones regionales. Los resultados para Alemania muestran que las regiones económicas funcionales tienden a capturar mejor la agrupación espacial que las administrativas. Sin embargo, las regiones económicas funcionales, especialmente aquellas alrededor de los centros metropolitanos, no pueden explicar una cantidad considerable de agrupaciones a un nivel de agregación inferior. Además, las regiones económicas funcionales, que representan bien las interrelaciones de desplazamiento al trabajo, capturan peor la homogeneización espacial que otras delimitaciones económicas funcionales.

**抄録:** 本稿では、経済的機能区域が、行政区画よりもコア経済指標の空間的クラスタリングをよく捉えるかどうかを検討する。そこで、階層的線形モデルを使用し、異なる区域の均質化の程度を測定する。ドイツの結果は、経済的機能区域は、行政区画よりもコア経済指標の空間的クラスタリングをよく捉えることを示す。しかし、低い集積レベルでは多数のクラスタリングがあるが、経済的機能区域、特に大都市中心部の周辺には重要ではない。さらに、経済的機能区域は、通勤の相関性を描出するが、他の経済的機能区域よりも空間的均質化を捉える性能が低い。