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Demographic Ageing and the Polarization of Regions - An Exploratory Space-Time Analysis*

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Abstract

Demographic ageing is expected to affect labour markets in very different ways on a regional scale. Contributing to this debate, we explore the spatio-temporal patterns of recent distributional changes in the worker age structure and innovation output for German regions by conducting an Exploratory Space-Time Data Analysis (ESTDA). Besides commonly used tools, we apply newly developed approaches which allow investigating joint dynamics of the spatial distributions. Overall, we find that innovation hubs tend to be located in areas with high skill concentrations, but also seem to coincide with favourable demographic age structures. We show that these concentrations are persistent over time due to clusterwise path dependence and spatial contagion forces. The spatio-temporal patterns speak in favour of a demographic polarization process of German regions where the post-reunification East-West divide is increasingly turning into a rural-urban divide.

Keywords: innovation, demographic ageing, exploratory space-time analysis, regional disparities, spatial polarization

JEL: J11, O31, R11, R12, R23

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1 Introduction

Demographic ageing has increasingly become one of the most pressing challenges that industrialized economies are facing in the 21st century. According to the latest Eurostat projections for the next 50 years, workforce ageing will continue in all European countries, though its magnitude, speed and timing are likely to vary. Demographic trends have raised the concern that an ageing workforce may increase existing regional disparities in a global, knowledge-based economy, as innovation potential is likely to depend on the age structure of local workers. One reason is that innovation activity is strongly concentrated in agglomerated areas due to advantages derived from externalities due to the colocation of specific industries (localisation economies) and the accessibility of firms to a variety of skilled workers (urbanisation economies). Particularly young and educated workers are attracted to urban areas and thick labour markets due to cultural amenities and better career opportunities (Moretti, 2011; Buch et al., 2014). This may further increase existing disparities, as urban areas that are already good at attracting human capital and good jobs tend to attract even more. In contrast, rural areas suffering from depopulation further diminish their human capital base (brain drain).

Whereas such divergence process has been demonstrated for US labour markets (Moretti, 2012), such phenomena are less clear for the German and, more generally, European markets with limited worker and firm mobility relative to the US.[1] Moreover, Germany is an interesting case of study due to its strongly ageing workforce and a large demographic divide. Spatial imbalances may have been reinforced by increasing labour-force participation of women who, seeking job opportunities, have increasingly been moving to prosperous urban areas. This trend has affected fertility patterns across regions and may further aggravate the rural-urban divide. Eastern regions have been suffering strongly from an ageing workforce due to age- and gender-selective out-migration. However, understanding the role of agglomeration forces in triggering a self-reinforcing process towards polarization might be interesting beyond the German case. For instance, Puga (2002) provides a discussion, based on location theories, of the possible (negative) causes of polarization within European countries, highlighting, for example, the role of transport infrastructure.

The objective of this paper is to contribute to this debate and explore the spatial and temporal

[1] Südekum (2008) investigates the spatial variation of human capital across West German regions for a historical time period showing that concentration forces are much lower compared to the US. However, he focuses only on qualification degrees and it is unclear how these forces are developing lately, especially as Germany is moving towards an aging knowledge-based economy.

patterns of knowledge production and demographic measures by means of an Exploratory Space-Time Data Analysis (ESTDA) to yield insights into recent demographic trends and how they may change the regional innovation landscape. There are several studies that have already explored the spatial distributions of economic performance or income across European regions using local and global measures of spatial association (Le Gallo and Ertur, 2003; Ertur and Koch, 2006; Dall'erba, 2005; Patacchini and Rice, 2007). However, these studies use more general indicators of economic performance and consider space-time dynamics only partially. Exceptions are a study by Le Gallo (2004) and more recent studies by Hierro et al. (2013) and Fazio and Lavecchia (2013), which deal with the persistence of regional disparities by exploiting spatial transition probabilities. We build on this literature and extend these approaches by newer visualisation methods for a comprehensive ESTDA of our innovation and demographic measures.

In particular, our contribution is fourfold. Firstly, we describe the spatial distribution of regional age structure, human capital and innovation performance in the interesting case of a fastly ageing Germany and discuss the possible theoretical links between these variables. We thereby do not focus only on the average age of workers, but also consider age diversity in order to capture a wider picture of the workforce age distribution. Secondly, we use a rich data set from the European Patent Office (EPO) that includes all published patents in Germany. By focusing on patents as one direct measure of the innovation process at the regional level, we are better able to capture innovativeness than more general indicators of economic performance such as productivity and economic growth. Furthermore, by including the share of creative professionals in our analyses we additionally explore one of the most important drivers of regional innovation (Florida, 2002; Florida and Gates, 2003). Thirdly, instead of only using static (spatial) methods such as Local Indicators of Spatial Association (LISA), we apply new visualization tools such as directional Moran scatterplots, developed by Rey et al. (2011), which allow investigating the space-time dynamics of spatial distributions, and help to detect a potential reinforcement of clustering and polarization. In addition, we calculate LISA transition probabilities as suggested by Rey (2001) to study the persistence of regional disparities. To our knowledge, this paper is the first to combine all the above methods and provide a comprehensive ESTDA on the themes of labour force ageing and innovation output. Finally, the paper contributes to the discussion on East-West convergence (divergence) after reunification which, after almost 25 years, still has important consequences for the theory and the design of policies in the demographic context.

Overall, our study shows that location matters in an aging knowledge-based economy as

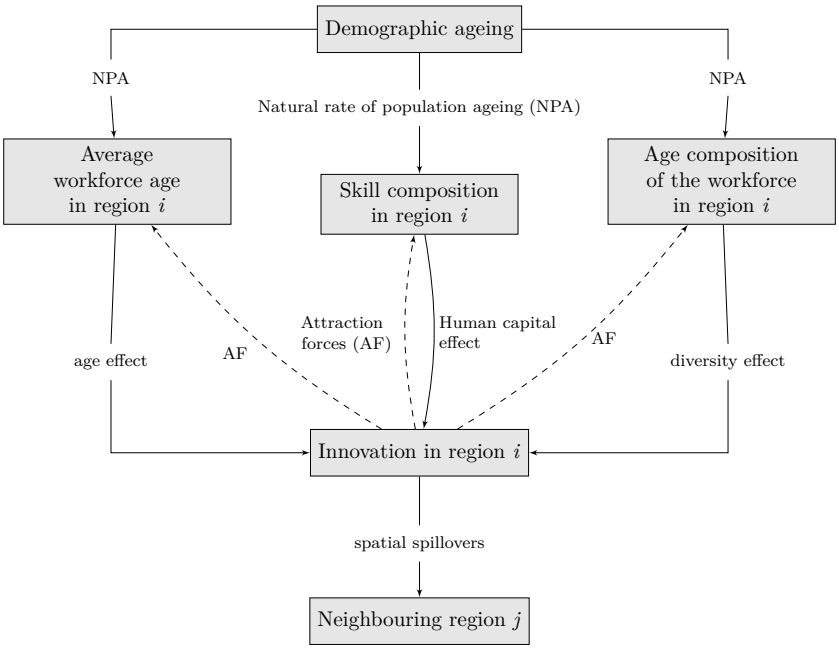
suggested by the detected spatial concentrations. In particular, we find that innovation hubs tend to be located in areas with high skill concentrations, but also seem to coincide with favourable demographic age structures. The study further demonstrates the persistence of these concentrations over time as indicated by clusterwise path dependence and spatial contagion forces in shaping the distributions. Moreover, the spatio-temporal patterns speak in favour of a demographic polarization process of German regions. According to our results, the post-reunification East-West divide is increasingly turning into a rural-urban divide. Whereas most urban regions are increasingly shaping a young and age-diverse workforce, most rural regions in both East and West Germany are affected by out-migration of their youngest cohorts.

The paper is structured as follows. First, we discuss the potential theoretical mechanisms of demographic polarization trends before introducing the database in Section 3. In Section 4 we then conduct an ESDA by first testing for spatial randomness (*global* Moran' I) and describing patterns of spatial clusters and outliers (*local* Moran' I). In Section 5 we then move to the space-time dynamics by investigating changes in the spatial clusters over time (directional Moran Scatterplots) and path-dependencies (LISA Transition matrices). Finally, Section 6 concludes.

2 The Polarization of Regions

There are several channels through which demographic ageing may affect the competitiveness of regions and thus, ultimately, increase regional disparities. As Figure 1 illustrates, the natural rate of population ageing does not only change the average age, but also shapes the age composition of the regional workforce through regionally differentiated fertility rates, changes in average life expectancy as well as differences in labour force participation rates. This may have several consequences for the production of knowledge in a region. On the one hand, an increasing average age may have a diminishing effect on the creativity of workers (age effect), which is known to decline with age (Simonton, 1988; Bratsberg et al., 2003; Jones, 2010). On the other hand, regions with increasing cohorts of older workers may even profit from an ageing workforce (diversity effect) if they develop a favourable age composition. The reason is that older workers are endowed with specific experience and (tacit) knowledge that may be complementary to the one of younger workers, as shown by a recent study at the regional level by Arntz and Gregory (2014). Moreover, there might be an indirect effect of demographic ageing on regional innovation through changes in the human capital base (human capital effect) arising, for instance, from

Figure 1: Channels through which demographic ageing may trigger a trend towards more polarized regions



older and formally more skilled worker cohorts (especially in the East) retiring and younger workers entering the labour market. The fact that the human capital base is an important driver of knowledge production and regional growth has been stated in various research (Lucas, 1988; Florida, 2002; Florida and Gates, 2003). The overall impact of these channels on regional knowledge production is, however, far from clear. The few existing studies at the country or regional level suggest a negative impact on GDP growth (Lindh and Malmberg, 1999; Brunow and Hirte, 2006) and total factor productivity (Feyrer, 2008). In contrast, Arntz and Gregory (2014), who use patent counts and citations, show that the overall impact of workforce ageing must not necessarily be negative, once the endogeneity of regional workforces is controlled for.

Given the overall effect, agglomeration forces then set in and reinforce existing disparities by pushing firms and skilled labour towards the innovation hubs, while leading to depopulation and brain drain in rural areas. The reasons for such spatial agglomerations are higher productivity and wages (Glaeser et al., 1992; Rauch, 1993; Ciccone and Hall, 1996) arising from local externalities (localization and urbanization economies). Skilled, young and more mobile workers in particular are attracted to urban areas, which offer several advantages such as cultural amenities and better career perspectives (Moretti, 2011; Buch et al., 2014). Note that such in-migrants may originate from both other regions within the country and from abroad.[2] Spatial clustering in

[2] A study by Poot (2008) discusses several reasons why immigration may affect regional competitiveness in the

knowledge production and human capital then occurs through localized knowledge spillovers (Jaffe, 1989; Audretsch and Feldman, 2004) and population relocation to surrounding urban counties (suburbanization). Overall, the above mechanisms may trigger a cumulative process towards increased polarization. This hypothesis is supported by several studies in the migration literature that show how selective migration, induced by interregional differences in wage and employment opportunities (Arntz et al., 2014) may lead to increasing spatial inequalities (Kanbur and Rapoport, 2005; Fratesi and Riggi, 2007) rather than serving as a re-equilibrating mechanism. In the next sections we explore the spatial distributions of innovation and demographic measures in the case of Germany in order to provide insights on the empirical relevance of such agglomeration and regional polarization tendencies.

3 Innovation and Demographic Measures

The present study focuses on workforce rather than population data, since we assume the regional age structure to affect regional innovation mainly through the working rather than overall population. For the calculation of the workforce age structure, we exploit the regional file of the Sample of Integrated Labour Market Biographies (SIAB) from the Institute of Employment Research (IAB) for the years 1995-2008. The data set is an employment subsample provided by the German Federal Employment Agency and contains information on workers that are subject to social insurance contributions by their employers, thus excluding civil servants and self-employed individuals. The data includes individual employment histories on a daily basis and contains, among others, information on the age and occupations of workers. We use annual cross sections at the cut-off date of 30 June and calculate regional indicators of demographic composition including average age, age dispersion (standard deviation) and the share of creative professionals[3] (which we will refer to as our human capital base or skills). We restrict the analysis to full-time employed individuals subject to the social insurance contribution, that is, excluding minors and unemployed workers.[4] Furthermore, we restrict our data set to working individuals between 18 and 65 years of age to avoid selection problems that would be associated, for instance, to the fact that those few underage workers are undergoing a vocational training. As a regional definition, we use the 332 labour market regions defined in the regional file of SIAB data. These regions

context of demographic ageing.

[3]For the classification of creative professionals, we follow Möller and Tubadji (2009).

[4]We hypothesize here that part-time workers are equally employed across regions.

reflect aggregated counties to the extent that they comprise at least 100,000 inhabitants. We focus on this detailed regional level instead of using more aggregated labour market regions in order to distinguish between different degrees of urbanization.

As a measure of regional innovativeness, we use patent data which are provided by the European Patent Office (EPO). The use of such direct outcome measures is still rare in the literature dealing with the effects of ageing workers on competitiveness, especially in regional level studies[5], but should be able to better capture innovativeness than more general indicators of economic performance. Our data set contains patent data both at the applicant and inventor level. Whereas the applicant (quite often, the firm) is the holder of the patent right, the inventors are the actual inventors cited in the document. We focus on patent inventors, since we are interested in their spatial distribution rather than in the location of the formal holder, which is often one of the firm's headquarters. Since patents may have been developed by serval inventors located in different regions, we apply a fractional counting approach to assign to every region the respective share of the patent. For instance, an inventor who developed a patent in Mannheim with one further individual working abroad would generate 0.5 patents for this region. Following this procedure for each of the 332 regions, we calculate the number of patent applications for the years 1995-2008. Since the number of inventions of a region may simply reflect its size rather than the knowledge production efficiency, we furthermore condition the number of patents (multiplied by 100) by the number of employed workers of the region, obtaining a measure of patent production per 100 workers.

There are several advantages and disadvantages of using patenting data at the regional level (Giese and von Reinhard Stoutz, 1998; Giese, 2002). On the one hand, patent applications are a useful indicator of research and invention activities at the local level, as they include information on the origin of inventor activities, that is, the place of residence and therefore, indirectly, the approximate location of the research institute. On the other hand, not every invention becomes the subject of a patent application, nor does a patent necessarily become a marketable product or process. Moreover, the reasons for a patent application may not only rest on protecting an invention against unjustified use, but may reflect strategic concerns such as securing and extending regional markets, prestige advertisement and the demonstration of innovative capacity to economic counterparts (e.g., shareholders or funding partners). Despite these disadvantages, empirical evidence by Acs et al. (2002), who provide an exploratory and a regression-based

[5]See, for instance, Brunow and Hirte (2006), Feyrer (2008) and Lindh and Malmberg (1999).

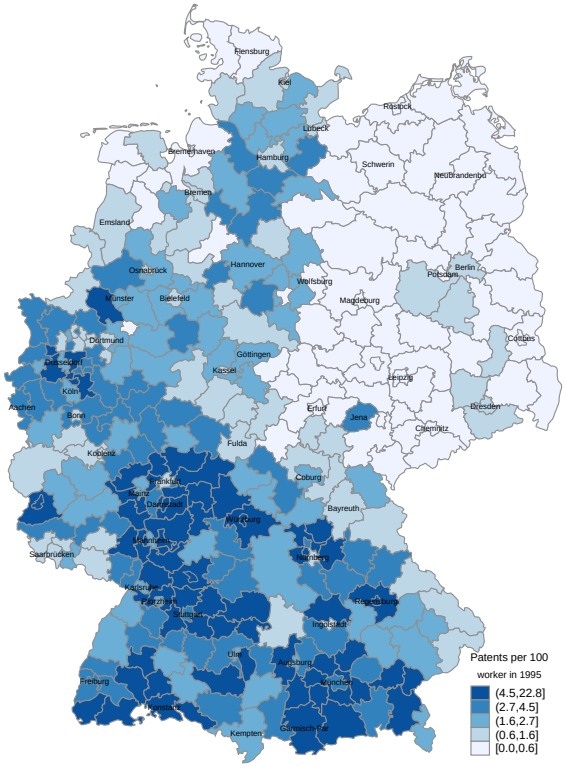
comparison of the innovation count data and data on patent counts at the lowest possible levels of geographical aggregation, suggests that patents provide a fairly reliable measure of innovative activity. Similarly, a survey study by Griliches (1998) concludes that patents are a good indicator of differences in inventive activity.

Figure 2 maps patents per 100 worker and average workforce age for our 332 regions for the initial year as well as the absolute change between 1995 and 2008. Similar maps for workforce age dispersion and the share of professionals are shown in Appendix A.1. For instance, the first quintile in Figure 2a (light blue) depicts the first 20% of least innovative regions in 1995, whose values range from 0.2 to 1.4 patents per 100 workers. The fifth quintile (dark blue) contains the 20% most innovative regions. The maps show that innovations are mostly generated in urban counties around West German cities such as Duesseldorf, Frankfurt, Stuttgart, Freiburg, Nueremberg and Munich. These regions also employ most creative professionals. In contrast, only a few East German major cities such as Jena were halfway competitive in the production of knowledge a few years after reunification. The spatial distribution of average age further reveals that only a few West German regions exhibit relatively old workforce, including major cities and urban counties around Kiel, Hamburg, Bremen, Hannover, Duesseldorf, Frankfurt, Stuttgart, Nueremberg and Munich. The fact that most rural regions in West Germany comprise relatively young and age-diverse workforces reflects historically large shares of conservative farming families with traditional role models that led to relatively high fertility rates, particularly in Bavarian and North-Western counties (around Emsland). In contrast, East German regions depict relatively old and homogenous workforces indicating that plant closures and out-migration of young workers after reunification strongly affected their age structure. The latter has already been confirmed by Burda and Hunt (2001) and Hunt (2004), who study the years between reunification and the millennium and find that East-West migrants tend to be young and better educated compared with stayers.

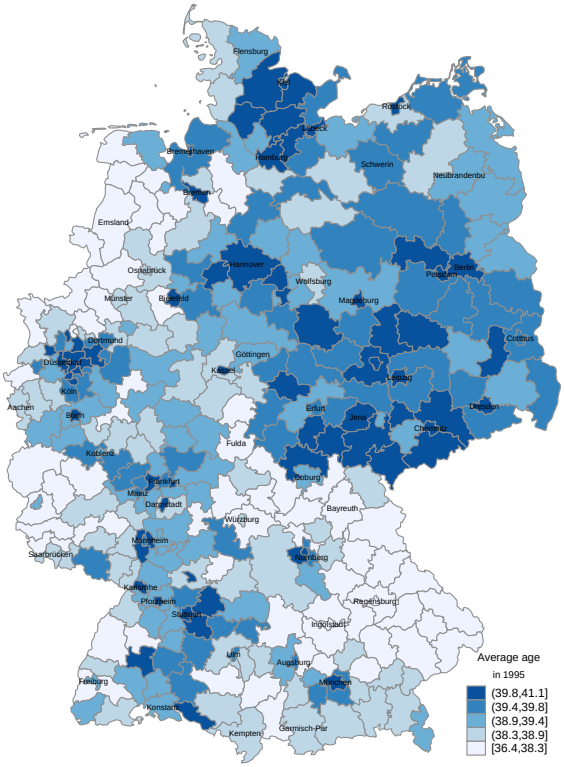
However, looking at changes over time (during the 14-year period considered here) suggests that the East-West divide is turning into a rural-urban divide (see Appendix A.2 for a map of German regions by agglomeration status). Whereas urban areas were able to hold their average age constant during the last 14 years, rural regions in both parts of the country experienced a strong demographic ageing process, with increases in their average age up to 5.2 years. These developments also reflect rising labour force participation of women during the last 30 to 40 years. In particular, young and qualified women increasingly find better career perspectives in

Figure 2: Regional quantile maps for innovation and average workforce age for the initial year 1995 and absolute changes between 1995-2008

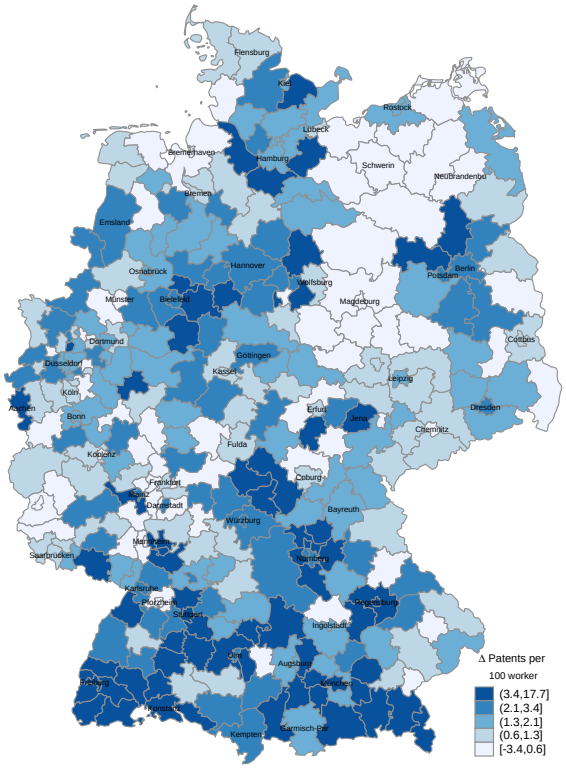
(a) Patents per 100 workers in 1995



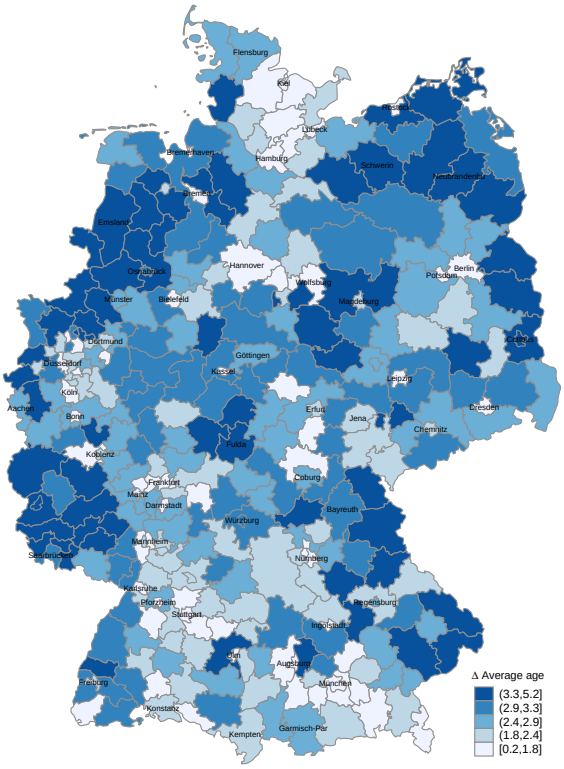
(b) Average workforce age in 1995



(c) Δ Patents per 100 workers



(d) Δ Average workforce age



urban areas, thus depressing the fertility rates of rural regions (in addition to depopulation). This is particularly true for East Germany that comprises many rural counties. Overall, these findings already indicate spatial dependencies in the ageing and innovation processes, as many regions seem to have experienced a similar trend to their surrounding regions. As discussed in Section 2, this might reflect agglomeration forces that are reenforcing existing spatial inequalities and which may lead to a polarization of regions. In order to shed light on these deep economic forces, we thus explore spatial regimes and investigate the space-time dynamics of the spatial distributions in the next section. Such an analysis enables the detection a potential reinforcement of clusters and spatial polarization tendencies.

4 Global and Local Spatial Autocorrelation

In the present section, we test the hypothesis of spatial randomness using the *global* Moran's I (MI) statistic and use Local Indicators of Spatial Association (LISA) to visualize *local* patterns of spatial associations (clusters). We conduct the static analysis for the initial year 1995, a few years after reunification, as a benchmark for the following analysis. In Section 5, we then analyse the space-time dynamics of the observed spatial clusters (or outliers) across the period 1995-2008. The latter will also allow to reveal potential distributional shifts in Eastern Germany due to the transition from a communist system to a market economy and where agglomeration forces might have started to set in and shape the spatial patterns of our innovation and demographic measures.

4.1 Global spatial autocorrleation

Since the distribution of workers cannot be expected to be random in space, we test for global spatial autocorrelation using the MI indicator, which provides a single summary statistic describing the degree of clustering present in spatial data. In particular, it allows implications on whether, for instance, highly (lowly) innovative regions are often surrounded by regions that are also highly (lowly) innovative. This is interesting, since it reflects agglomeration forces and spatial spillovers. Moreover, it allows to classify whether a region is part of a relevant cluster, such as a hot (cold) spot, or rather an outlier. Note that this information can be used in any regression analysis as a proxy for e.g. knowledge spillovers between regions.

We first define the structure of the spatial relationship by considering a spatial weights matrix

based on rook contiguity that assumes neighbouring relationships between regions by shared borders.[6] The spatial weights matrix provides information on the spatial proximity between each pair of locations i and j, while the diagonal values of the weights matrix are set to zero. We standardize the matrix so that the elements of each row sum to one (row-standardization).[7] We define the spatial lag of a variable y_i in region i as the average value of a variable evaluated at its neighbouring units. We then construct a bivariate scatterplot with standardized values y_i on the horizontal axis and their spatial lags $\sum_{j=1}^{N} \widetilde{W}_{ij} y_i$ on the vertical axis (Moran Scatterplot, see Figure 3). As a covariance and correlation measure we consider the Moran's I statistic, which constitutes a measure of the overall spatial dependence.[8] The MI can be interpreted as a regression coefficient resulting from the regression of the spatial lag $\widetilde{W}_{ij} y_i$ on y_i (Anselin, 1996). Values of I greater (smaller) than $E(I)$ indicate positive (negative) spatial autocorrelation.

Figure 3 shows the Moran Scatterplots for the demographic and innovation measures. Each of the points in Figure 3 represents a combination of a regions' value in 1995 and its corresponding spatial lag. The values on the x- and y-axes are standardized so that the vertical and horizontal lines represent the national values and divide the scatterplot into 4 quadrants that correspond to the following four different types of spatial association (anticlockwise from top right): high-high (HH), low-high (LH), low-low (LL) and high-low (HL). For instance, a HH region exhibits a high number of patents per worker and is surrounded by regions that exhibit a high number of patents as well. Both HH (hot spots) and LL (cold spots) represent regimes of positive spatial association, whereas LH and HL indicate negative association. The calculated MI for global autocorrelation is represented by the slope of the line interpolating all points in the scatterplot since it is based on standardized values.

Figure 3 shows for all variables significant degrees of spatial autocorrelation. Most regions are either in the first (top right) or third quadrant (bottom left). Note that the last row in the Appendix A.3 summarizes the total amount of regions in each quadrant. For instance, in the case of patents per worker, almost 30% of all regions (98 out of 332) fall into the first quadrant and 50% in the third. Interestingly, the points agglomerate dominantly in the third quadrant

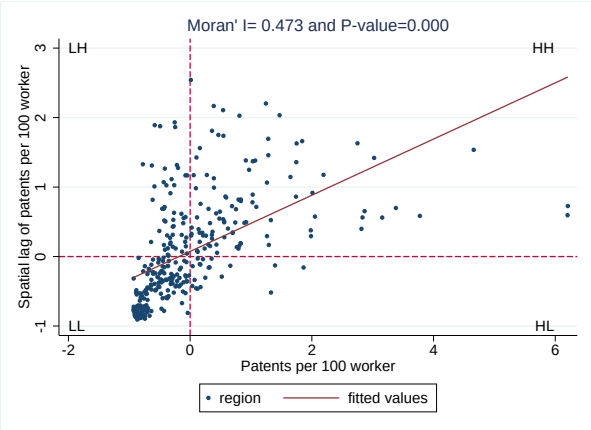
[6] As recently shown in the literature (e.g. see Patuelli et al. 2012), the choice of the spatial weights matrix is often of little importance, since different geography-based matrices tend to have strongly correlated weights. In a regression framework, multiple matrices may be tested ex post, for example by means of Bayesian model comparison (LeSage and Pace, 2009).

[7] The elements of the standardized weights matrix are defined as follows: $\widetilde{W}_{ij} = W_{ij} / \sum_{j=1}^{N} W_{ij}$, where $W_{ij} = 1$ if i and j are defined as neighbours and $W_{ij} = 0$ if otherwise.

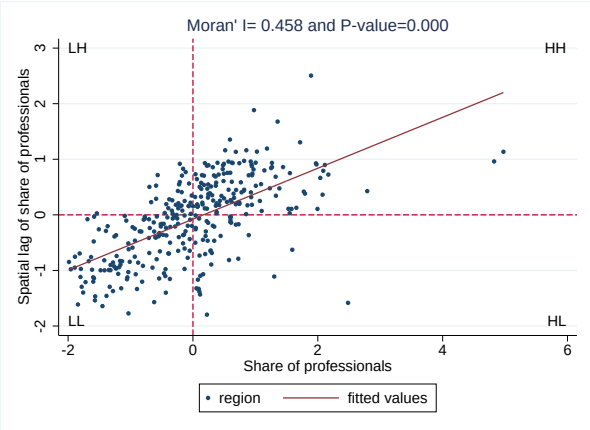
[8] We define the MI as follows: $I = N/S_o(\sum_{i=1}^{n} \sum_{j=1}^{n} \widetilde{W}_{ij}(y_i - \bar{y})(y_j - \bar{y}))(\sum_{i=1}^{n}(y_i - \bar{y})^2)$ for $i \neq j$, where $S_o = \sum_{i=1}^{n} \sum_{j=1}^{n} \widetilde{W}_{ij}$.

Figure 3: Moran's I scatterplot for patents per 100 workers, average age, age dispersion and share of professionals in 1995

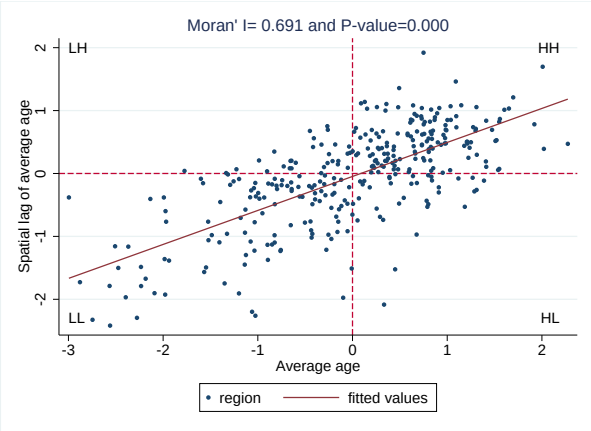
(a) Patents per 100 workers



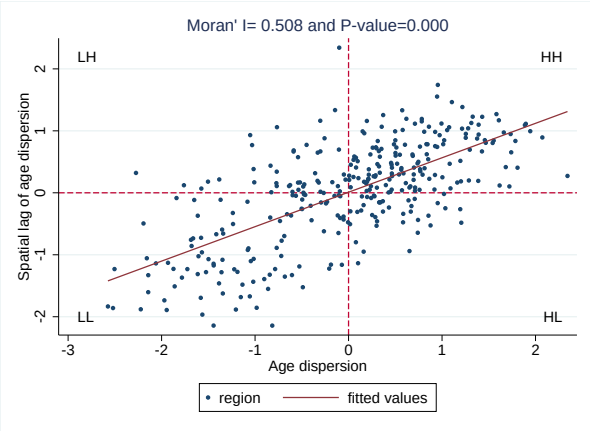
(b) Share of professionals



(c) Average age



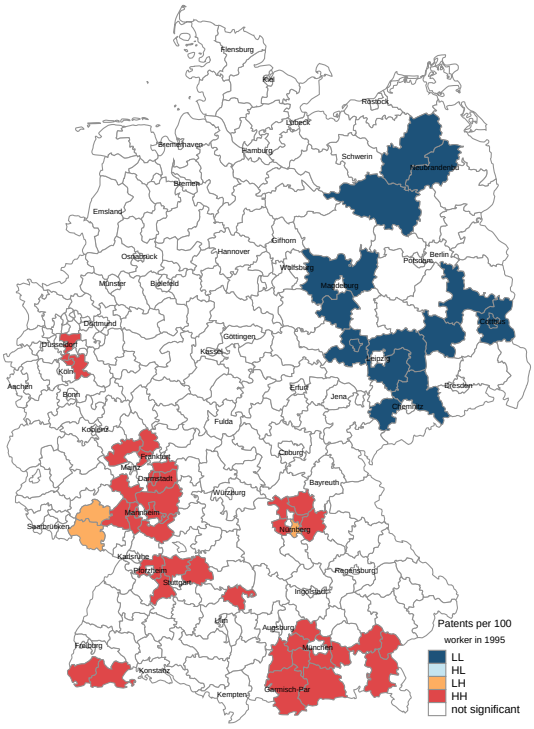
(d) Age dispersion



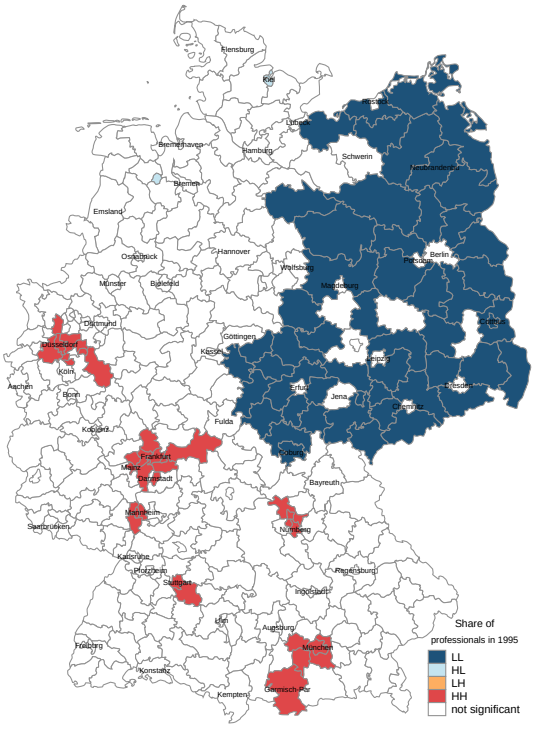
and become more dispersed with increasing values. This result indicates large clusters of scarcely productive regions, whereas clusters of highly productive regions seem rare. Compared to the US, for instance, the concentration of high-tech industries thus seems less. A clearer indication of clustering is found for average age, for which positive spatial association appears to be wide, in terms of both higher and lower values. According to Column 5 in Table A.3, 40% of regions fall into the first quadrant and a similar fraction into the third. The pattern is similar and stronger for age dispersion and the share of creative professionals, thus indicating spatial concentrations of young and diverse workers in creative occupations. These observed patterns are statistically significant according to the MI coefficients, which are all above zero.

Figure 4: LISA cluster maps for patents per 100 workers, average age, age dispersion and share of professionals in 1995

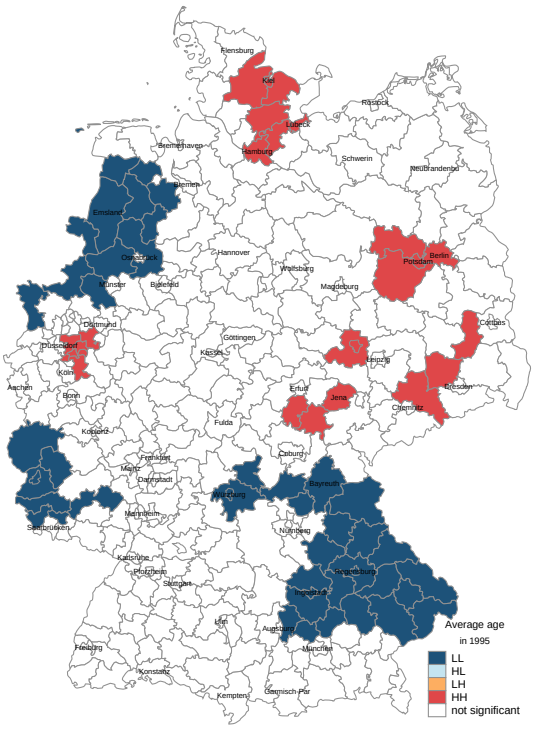
(a) Patents per 100 workers



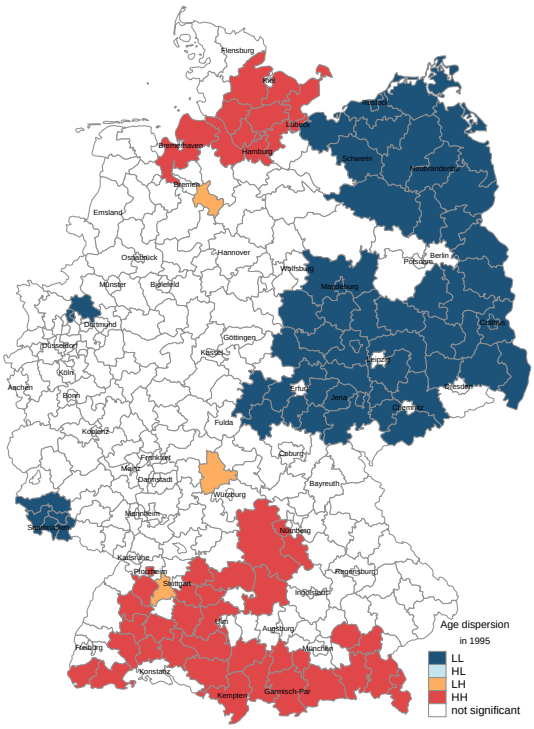
(b) Share of professionals



(c) Average age



(d) Age dispersion



4.2 Local Indicators of Spatial Association

In the present section, we aim to locate the observed clusters and assess their spatial extent. Since these questions cannot be answered by means of global measures of spatial autocorrelation, we use Local Indicators of Spatial Association (LISA) as proposed by Anselin (1995). The local version of MI gives an indication on the significance of local spatial clustering for each region.[9] Similarly to the global MI statistic, significance can be determined through the expected value and variance. The interpretation is similar. A positive LISA indicates clustering of HH or LL values in and around i, whereas a negative LISA indicates a spatial outlier, that is either HL or LH.

Figure 4 shows the LISA cluster maps (again for the initial year 1995) for our four variables and where only values that are significant at the 5% level are presented. The maps reveal a large East-West divide. In particular, they show large clusters of lowly innovative regions in rural and sparsely populated counties in East Germany around Neubrandenburg, Magdeburg, Leipzip, Chemnitz and Cottbus. In contrast, the innovation hubs are located in mostly urban counties in Western and Southern Germany around Duesseldorf, Frankfurt, Mannheim, Stuttgart, Freiburg, Nueremberg and Munich. There is almost no significant outlier, indicating that regions are unlikely to be a high (low) innovative region in a low (high) innovative cluster. Moreover, these high-tech clusters coincide with spatial concentrations of creative professionals. According to our contingency tables displayed in Appendix A.3, 80% of all (significant and insignificant) regions in an innovation hub coincide with professional worker hotspots. In contrast, about 65% of all low innovation clusters coincide with low skill concentrations.

Looking at the LISA cluster maps for average age shows surprisingly few significant clusters of old regions in Eastern Germany. Particulary rural regions still seem to profit from historically high fertility rates. After reunification, the almost entire Eastern workforce constitutes one large cluster of age-homogenous regions. Considering West Germany, there are only two old-age clusters in the Ruhr district, which has been struggling with its structural change and around Kiel in Northern Germany, whereas almost all Bavarian regions in Southern Germany and regions around Emsland in North-Western Germany show young worker concentrations. The latter reflect areas of prosperous growth with a specialisation in the agricultural sector. Clusters of age-diverse regions are mostly located in Southern and Northern Germany and reflect regions

[9] We define the local MI as follows: $I_i = (\sum_{j=1}^{N} \widetilde{W}_{ij}(y_i - \bar{y})(y_j - \bar{y}))(\frac{1}{N}\sum_{j=1}^{n}(y_i - \bar{y}))$.

with a relatively balanced mix between young and older cohorts. Many of these regions are also part of an innovation hub as indicated by the contingency tables.

Overall, the investigation of local and global spatial autocorrelation underlines the importance of spatial dependencies. In particular, LISA analyses indicate that innovation hubs tend to be located in areas with high skill concentrations, as one would expect, but also seem to coincide with a favourable demographic age structure. One explanation may be that high-tech clusters tend to be very successful in attracting young workers and shaping an age-diverse workforce by keeping the older and more experienced ones in the labour force. As discussed in Section 2, this might in turn increase the innovation potential of these regions even further. In fact, agglomeration externalities seem to have not reached their upper bound yet, as indicated by limited concentrations of innovators. In contrast, we observe strong negative clustering of lowly inventive and unattractive areas in Eastern Germany that are facing considerable difficulties in coping with the transition to the innovation sector and that are lacking a (creative) human capital base.[10] These regions are particularly old and homogenous age-wise. However, since the patterns describe the initial situation after reunification, it remains to be shown how these clusters (and the large East-West divide) developed during the observed 14-year period and whether the existing disparities have lead to a spatial polarization trend as agglomeration theories would suggest.

5 Space-Time Dynamics

So far, we have gained insights into the spatial dimension of the data distributions, measured by the values of the initial year 1995. We are now interested in how such distributions evolved over time and whether there are any observable trends. Furthermore, we investigate the stability of the observed spatial patterns over time to reveal potential path dependencies. Most studies analysing the evolution of a variable's spatial distribution visually compare different geographical maps for separate points in time. Such approaches make it very difficult to analyse relative movements across time and space. For this reason, we apply new methods that are designed to address this limitation.

[10] This problem is exacerbated by the devaluation of the preexisting workers qualifications, especially for white-collar ones (e.g., in management, administration), which makes evaluating human capital in the former East Germany highly challenging.

5.1 Standardised Directional Moran Scatterplots

In this section, we investigate regional dynamics using Standardized Directional Moran Scatterplots (SDMS, Rey et al. 2011). For each variable, we calculate Moran Scatterplots for the years 1995 and 2008 separately (as described in Section 4) using relative values (to the national value). Note, that this time period is particularly interesting, due to the large second wave of selective migrants that moved from East to West Germany during the end of the 1990s, as discussed, for instance, by Arntz et al. (2014). This wave of migrants had its peak in 2001 and is expected to have changed the regional distribution of the workforce age structure. We plot each region's value in 1995 and 2008 into the same Scatterplot and connect both points to receive directional movement vectors.[11] All vectors are normalized by the 1995 national value to produce the SDMS shown in Figure 5. Whereas the arrowheads point to the regions' 2008 relative value, the vectors' starting point (at the origin) represents its corresponding value in 1995. The SDMS thus captures how a regions' position and spatial association developed between 1995 and 2008 relative to the national trend. For instance, a move of a region towards the first (HH) or third quadrant (LL) reflects the strengthening/emergence of positive spatial clustering (in a meliorative and worsening perspective, respectively) or the inversion of a previous opposite position (e.g., an LL region moving towards the origin, i.e., improving, will have a HH movement). On the other hand, movements towards the second (LH) or fourth (HL) quadrant reflect negative clustering tendencies (i.e., a local divergence process). The longer the movement vector, the larger the relative movement compared to the mean. As a robustness check we also calculated the average values for the periods 1995-1997 and 2006-2008 as alternative connecting points. Since the results did not change much, we stick to the former.

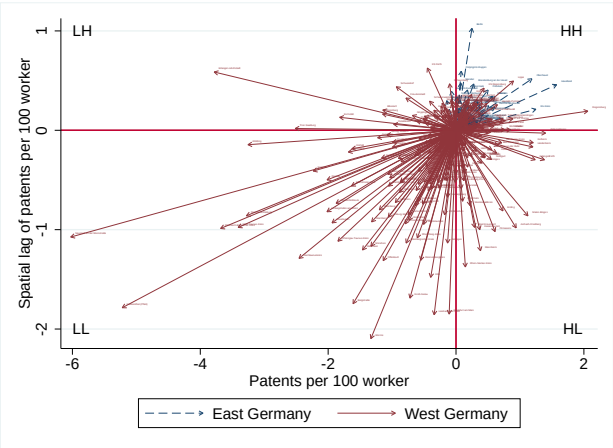
Figure 5 shows the SDMS for our four variables.[12] Movements of East German regions are shown in blue (dashed line), and West German regions are represented by in red (solid line). For patent production, the figures show large movements towards cold spots (movements towards the third quadrant). Among these are mostly urban counties around the West German metropolitan cities Frankfurt, Darmstadt and Ludwigshafen (e.g. Neustadt an der Weinstrasse, Darmstadt-Dieburg, Main-Taunus-Kreis), although some of these regions are moving from high

[11] We also checked the plots using the 3-year averages for the periods 1995-1997 and 2006-2008 as connecting points. Since the picture did not change much, we are confident that our results are not driven by exceptional occurrences in the years 1995 and 2008.

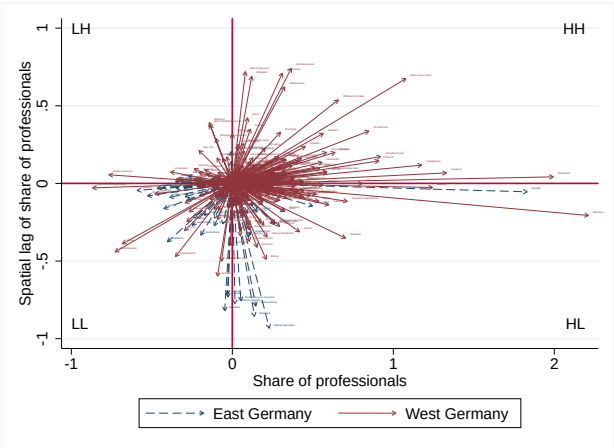
[12] For improved readability, we dropped Neustadt an der Weinstrasse and Frankenthal in graph (a) and Frankfurt am Main and Berlin in graph (d), since there target points lie far right and far left of all other regions.

Figure 5: Standardized Directional Moran Scatterplots for patents per 100 workers, average age, age dispersion and share of professionals (1995 to 2008)

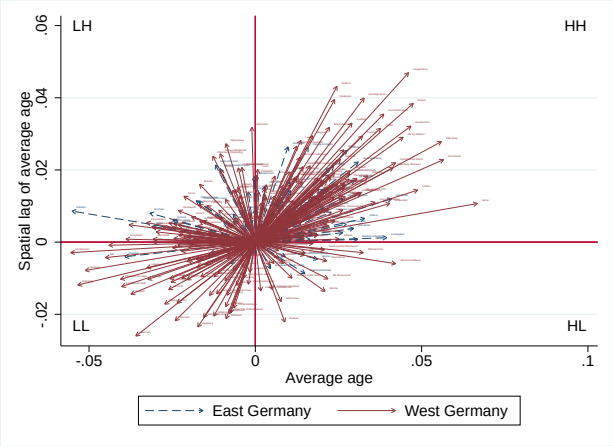
(a) Patents per 100 workers



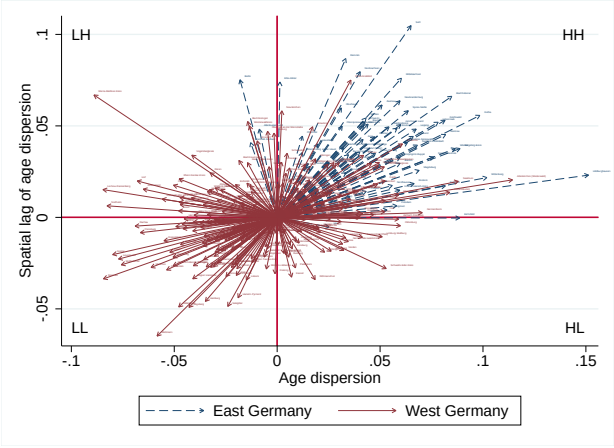
(b) Share of professionals



(c) Average age



(d) Age dispersion



initial values. In contrast, we observe only small relative movements towards innovation hot spots (movements towards the first quadrant) that are dominated by Berlin's peripheral regions Overhavel, Havelland, Barnim and Potsdam city. Also, Jena and its surrounding urban counties Weimar and Ilm improved in terms of creating high-tech clusters. These regions are increasingly successful in creating knowledge-based industrial districts. Their favourable developments are also reflected by their increases in the share of professional workers, despite the low average values of their surrounding neighbours (reflected by movements towards the fourth quadrant). Apart from these exceptional developments, East Germany as a whole is experiencing negative clustering tendencies with respect to creative professional shares, whereas almost all West German regions show higher skill concentrations. These findings suggest that, despite a small catching-up process for a few agglomerated areas, the overall degree of patenting and its geographical concentration remains low in Eastern Germany. In particular, Eastern regions are increasingly facing difficulties

in speeding up the accumulation of professional skills, despite their improvements in innovation. This may also help explaining why we find surprisingly limited evidence for positive co-movements of innovation and human capital concentration (see Appendix A.4).

Compared to our innovation measures, the SDMSs for the demographic variables reveal much stronger polarization tendencies. The dominant movements towards the first quadrant for average age are driven mostly by rural areas both in East and West Germany because of rural-urban migration of particularly young workers. In contrast, regions moving towards the third quadrant include major West German cities such as Munich, Stuttgart, Frankfurt, Hamburg. The latter developments may reflect suburbanization processes for which the existing cluster slowly spread beyond administrative borders to new regions. The results indicate an increasing concentration of young workers in cities, whereas rural regions are suffering from depopulation and ageing workers. Of course, since most peripheral regions are located in Eastern Germany (see Appendix A.2), this development mirrors the former divide between the two parts of the country. However, the concentration of younger workers have not coincided much with high-tech clustering, as suggested by our contingency tables. This is somehow surprising, and may reflect still low innovative regions (such as the Berlin suburbs) that have been relatively improving their innovation output, despite an ageing workforce. On the other hand, the figures also indicate that 44 (mostly West German) regions have been moving both towards lowly innovative and high-age clusters. The association between innovation and age dispersion is much clearer. In particular, an increasing clustering of age-homogenous regions (mostly rural regions in Eastern Germany) coincides with lower clustering of high-tech industries, whereas geographical environments with an increasingly age-diverse workers base (mostly young cities in Western Germany) seem to be quite successful in the generation of knowledge (spillovers).

Compared to the initial state (after reunification), where the almost entire Eastern economy reflected low innovation performance and ageing workers (relative to the West), the recent trends speak more in favour of a rural-urban divide. Whereas most urban regions are increasingly shaping a young and age-diverse workforce, almost all rural regions in both East and West Germany are affected by out-migration of their youngest cohorts. Since most Eastern regions constitute rural regions, they have been affected most by this trend, thus transitioning towards a age-homogenous economy with less mobile older workers. However, the results also reveal a decent catching up process of few Eastern regions around the recently agglomerating capital city and few other economic beacons in the East that have increased their innovation output, despite

an ageing workforce. These findings may indicate preliminary evidence of agglomeration forces (suburbanization processes) setting in after the economic transition and changing the spatial distribution slightly. Whether regions are able to turn the trend around or will rather remain in their state due to geographical contagion is something we will investigate by means of transition probabilities in the following section.

5.2 Space-Time Transitions

In this section we calculate LISA transition matrices in order to track the evolution of the investigated variables from a spatial clustering perspective. The method is based on the classical Markov chain approach, which allows to study time dynamics between different groups (e.g., quantiles). From a methodological viewpoint, the proposed LISA transition matrices are obtained similarly to the standard probability transition matrices. We follow Rey (2001) and investigate the transitions of regions between the four different types of spatial association outlined above (HH, LH, LL, HL) to allow a quantitative assessment of contagion effects. For a detailed technical explanation see Appendix A.5. The calculated transitions are shown in columns (1) to (4) in Table 1. Column (5) includes the share of regions in the different states at the beginning of the period, whereas Column (6) corresponds to the computed steady state shares (expected long-run equilibrium shares). For instance, the probability of a highly innovative region surrounded by highly innovative regions (HH) to remain in its current state over each time period (a year) is 90.3% (see row 1 and column 1), whereas the probability of remaining a LL region accounts to 93.6% on average (row 3 and column 3). All variables show fairly high off-diagonal probabilities. In particular, age dispersion shows relatively high transition probabilities reflecting high dynamics over time. The two transitions with the highest off-diagonal probabilities are generally those for regions moving from LH to HH and from HL to LL (negative contagion), that is, transitions where a region is 'infected' by the state of its neighbours (Hierro et al., 2013). This result thus indicates that it is highly likely, for an outlier, to become part of its surrounding cluster speaking in favour of strong contagion forces at place.

The probability of negative contagion is thereby higher compared to positive contagion, that is, it is more likely for an HL region to become LL than for an LH region to become HH. The only exception is the share of professional workers. This result stands in contrast to the one of Hierro et al. (2013) who stress that positive spatial contagion (transitioning from LH to HH) is more likely to be expected than negative contagion (from HL to LL). Finally, movements

Table 1: LISA transition probabilities for innovation and demographic measures (1995-2008)

Variable	Cluster/ Outlier in period t	Cluster/Outlier in period $t+1$ $(HH)_{t+1}$ (1)	$(LH)_{t+1}$ (2)	$(LL)_{t+1}$ (3)	$(HL)_{t+1}$ (4)	Initial shares in 1995 (5)	Steady state (6)
Patents per 100 worker	$(HH)_t$	90.3	6.3	0.5	2.9	29.5	28.3
	$(LH)_t$	12.1	79.6	8.1	0.2	15.4	15.6
	$(LL)_t$	0.4	2.6	93.6	3.4	49.4	48.1
	$(HL)_t$	8.4	1.9	20.7	68.9	5.7	8
Share of professionals	$(HH)_t$	94.9	4.2	0.0	1.0	14.5	16.9
	$(LH)_t$	2.8	0.1	95.0	2.1	17.8	24.5
	$(LL)_t$	0.0	1.1	97.2	1.6	55.4	46.9
	$(HL)_t$	1.4	0.0	6.8	91.8	12.4	11.7
Average age	$(HH)_t$	91.4	4.6	0.6	3.5	44.6	38.3
	$(LH)_t$	16.5	68.1	14.2	1.3	9.0	11.8
	$(LL)_t$	0.3	4.9	88.6	6.3	35.5	36.7
	$(HL)_t$	9.6	1.8	17.2	71.4	10.8	13.3
Age dispersion	$(HH)_t$	82.7	7.6	8.5	1.2	45.2	29.5
	$(LH)_t$	17.6	63.6	15.0	3.8	13.3	13.5
	$(LL)_t$	1.3	5.0	85.6	8.1	29.8	39.2
	$(HL)_t$	12.4	2.4	18.3	66.9	11.8	17.8

from LH to LL and from HL to HH seem fairly high as well in the case of average age and age dispersion. Obviously, single regions may also end up pulling their neighbours up/down to their status, but the probability of this occurrence is much lower. Thus, the probability to reverse the trend, for underperforming regions with an old and homogenous age structure, for instance in East Germany, is low. There appears then to exist a clusterwise 'path dependence', where it is not only a region's own history that influences its chances of modifying its status quo in the future. In fact, its surrounding environment plays a role in limiting the range of possible future outcomes, or in favouring different outcomes, when there is a mismatch between a region's state and the one of its surrounding areas. In particular, geographical areas facing a downward trend in terms of innovation performance and an ageing population are likely to pull other regions down as well. One reason for such geographical contagion forces might be age-selective outmigration, which has an impact on the demographic structure of neighbouring regions, as well as social networks and interregional ties. Clearly, such hypothesis may be further tested by means of regression modelling.

Furthermore, columns (5) and (6) of Table 1 show the initial shares of clusters/outliers in 1995 and the long-run ones suggested by our data, by means of the ergodic steady-state distributions. We find that most regions were either LL or HH in the initial period and this appears to be true in the long run as well. For instance, 29.5 (49.4)% of regions were in a highly (lowly) innovative

cluster in 1995 and the expected share in the long run is 28.3 (48.1)%. The probability of being part of a cluster - both highly and lowly innovative - is therefore expected to decrease. The latter finding may reflect the slow recent catching-up process of Eastern regions. Our results further suggest an increasing likelihood of staying or becoming a region with high professional worker shares or being located near such a cluster (enlargement of both HH and LH) whereas the opposite is true for low skill concentrations (shrinking of both HL and LL). Moreover, our demographic measures indicate that LL clusters will become wider, with a decrease in the size/number of the HH clusters. Put differently, an increasing share of regions will comprise a homogenous workforce which reflects the rural to urban migration of young workers and the depopulation of peripheral regions, particularly in Eastern Germany. This might also explain the increasing concentrations of young workers (in urban areas) as suggested by the steady state values.

Overall, the transition matrices presented above suggest that location matters for the evolution of regional innovation and of the workforce characteristics, in the sense that the evolution of a region depends strongly on its neighbouring regions. In particular, it is unlikely for a region to reverse its trend in a highly interdependent geographical environment, indicating clusterwise path dependence. Moreover, the evidence suggests that outlier regions face a high probability to become part of the surrounding cluster due to strong contagion forces.

6 Conclusion

This paper contributes to the debate on demographic change in Europe and the potential role of spatial dependencies and agglomeration forces in triggering a cumulative process towards more polarized regions. In particular, we explore the spatio-temporal dynamics of regional innovation output, workers demographics and the creative human capital base for Germany. We apply newly developed approaches in order to detect spatial regimes or other forms of spatial heterogeneity for the investigated variables as well as its spatio-temporal dynamics.

The detected spatial concentrations suggest that location matters strongly in the German context. In particular, we find that innovation hubs tend to be located in areas with high skill concentrations in Western and Southern Germany, but also seem to coincide with favourable demographic age structures. In contrast, we observe strong negative clustering of lowly inventive regions with ageing working populations in Eastern Germany. These regions are still transitioning

to a knowledge-based economy and are attempting to build up a human capital base. Transition probabilities indicate that these concentrations are likely to remain relatively stable due to a strong clusterwise path dependence as well as contagion forces in shaping the spatial distributions. Hence, it is not only a region's own history that influences its chances of modifying its status quo in the future, but also the surrounding environment that plays a role in limiting (or favouring) the range of possible future outcomes.

Temporal changes in the spatial concentrations further suggest that the former East-West divide is increasingly turning into a rural-urban divide. Whereas most urban regions are increasingly shaping a young and age-diverse workforce, almost all rural regions in both East and West Germany are affected by out-migration of their younger cohorts. Since most Eastern regions are rural, they have been affected most by this trend, thus transitioning towards age-homogenous economies with less mobile older workers. However, the results also reveal a catching up process of few Eastern regions around the recently agglomerating Berlin and a few other economic beacons in the East that have increased their innovation output, despite an ageing workforce. The findings might indicate first attempts of agglomeration forces setting in after moving from a communist system to a market economy. Our results are somewhat in contrast to other studies such as Südekum (2008) who explores historical data and finds that spatial concentrations in West Germany are not big enough to trigger a self-reinforcing spatial concentration. Looking at a broader set of variables for a more recent time period, our findings seem to suggest quite the opposite for the innovation sector in an aging economy where agglomeration and urbanisation seem to matter stronger. Overall, we can not confirm Friedman (2005)'s hypothesis of a "flat world", according to which location will become irrelevant in the globalized and highly connected world due to decreasing transport costs and advances in communication technologies.

Our results have several policy implications. First, local policymakers aiming at reducing spatial inequalities should take into account the role of agglomeration and contagion forces in the innovation process, as well as (sub-)urbanisation trends in affecting workforce dynamics of spatially contiguous areas. In particular, major cities are gaining importance for young and skilled workers because of thick labour markets and rich amenities (Moretti, 2011; Buch et al., 2014). Due to spatial contagion, regions are unlikely to reverse this trend. Rather, urban regions that are already successful in attracting a young and diverse human-capital base appear to further attract such workers and aggravate a positive feedback loop process. From a national perspective, promoting innovation activities in beacon regions (for instance in Eastern German)

with the aim of exploiting knowledge spillovers and (positive) agglomeration externalities might thus be more promising for the economy than turning around the trend in depopulating and less attractive rural areas. Widespread promotion of Eastern regions as done by the joint Federal Government/Länder scheme for "Improving regional economic structures (GRW)" could be revisited in this regard. At the same time, regional policy strategies might consider "big push" type of policies to move the region to a good equilibrium (Moretti, 2011; Kline, 2010) and trigger a self-reinforcing process in the positive direction. Furthermore, regions should cooperate more with other neighbouring regions in shaping an attractive metropolitan area for young workers, rather than competing against them. This might include alliances in the education system such as different universities with different specialisations, but which are complementary.

Our findings also have implications for future work in this field. In particular, our analysis may serve as a departure point for any analysis trying to measure the impact of demographic ageing on firm or regional performance. In particular, the causal relation between workforce ageing and a regions' innovation potential is still far from understood. Recent attempts by Arntz and Gregory (2014) move forward in this direction and explore the benefits of a more age-diverse workforce. The presence of strong clustering in the demographic variables, and of very specific outliers with regard to innovation, further suggests that spatial econometric techniques may be exploited when investigating such research question.

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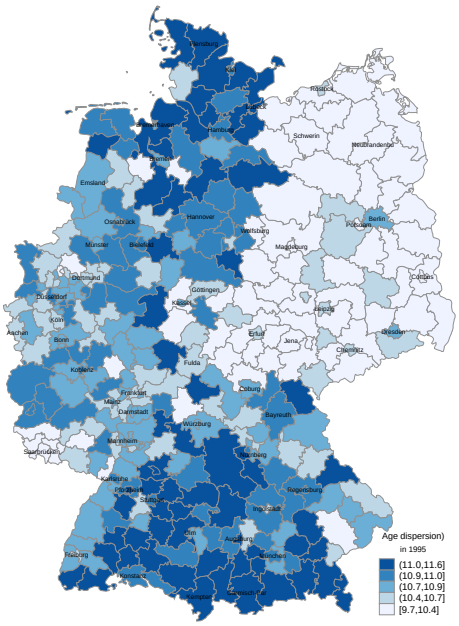
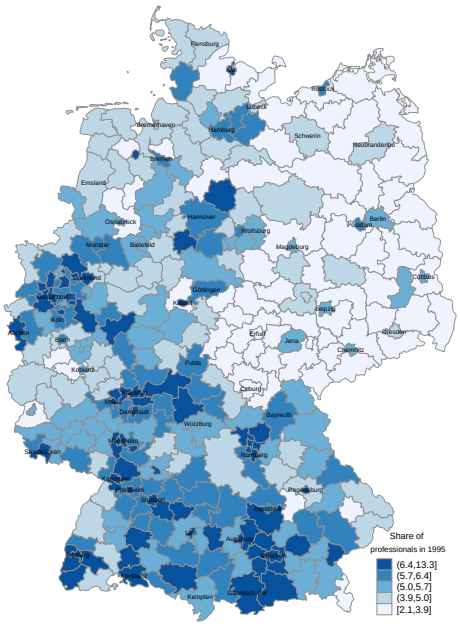
A Appendix

A.1 Regional quantile maps for workforce age dispersion and professional shares for the initial year 1995 and absolute changes between 1995-2008

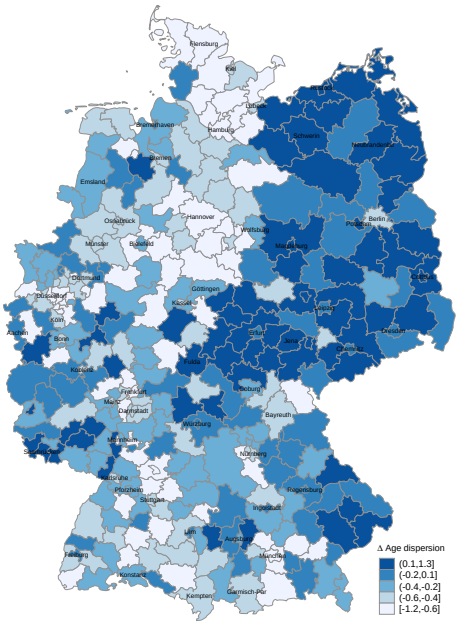
(a) Workforce age dispersion in 1995



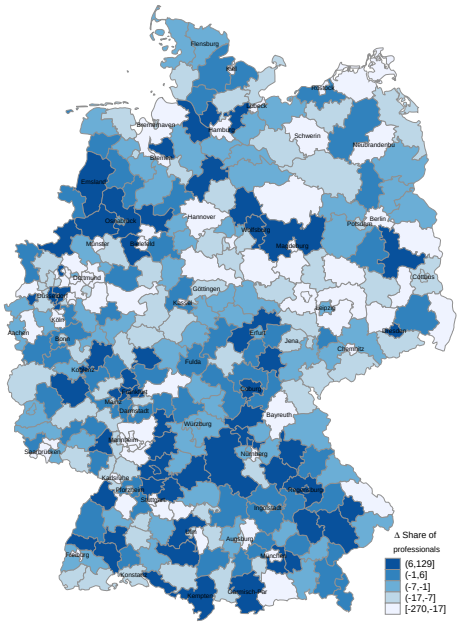
(b) Share of creative professionals in 1995



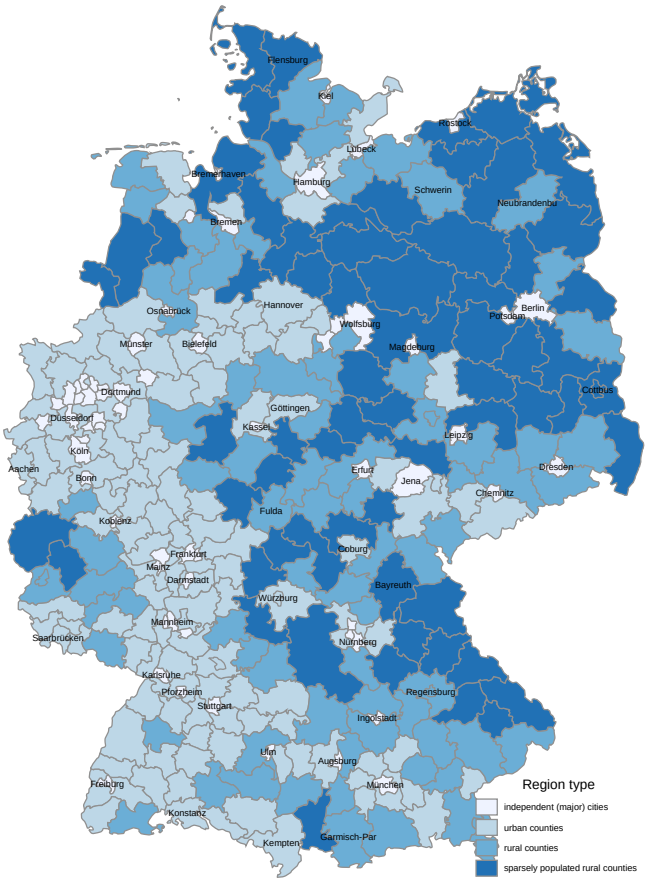
(c) Δ Workforce age dispersion



(d) Δ Share of creative professionals



A.2 Classification of regions according to their agglomeration status



A.3 Contingency tables for LISA cluster maps in Figure 4

Variable	Cluster/Outlier type	Patents per 100 workers				Total obs.
		High-High (1)	Low-High (2)	Low-Low (3)	High-Low (4)	(5)
Average age	High-High	37	13	94	4	148
	Low-High	10	3	16	1	30
	Low-Low	39	25	42	12	118
	High-Low	12	10	12	2	36
		Pearson $\chi^2 = 76.4687$ Pr $= 0.000$				
Age dispersion	High-High	59	27	51	13	150
	Low-High	18	10	15	1	44
	Low-Low	9	6	80	4	99
	High-Low	12	8	18	1	39
		Pearson $\chi^2 = 54.3235$ Pr $= 0.000$				
Share of professionals	High-High	77	29	14	8	128
	Low-High	15	8	10	1	34
	Low-Low	5	7	108	7	127
	High-Low	1	7	32	3	43
		Pearson $\chi^2 = 10.3431$ Pr $= 0.323$				
	Total obs.	98	51	160	23	332

Notes: The table reads as follows. The value in row (1) and column (1) indicates that 37 regions are both part of an innovation hot spot and old-age cluster, whereas the value in row (4) and column (1) means that 39 regions are part of a high-tech cluster and at the same time exhibit high concentrations of young workers.

A.4 Contingency tables between types of movements in the Standardized Directional Moran Scatterplots shown in Figure 5.1

Variable	Movements towards a Cluster/Outlier type	Patents per 100 workers				Total obs.
		High-High (1)	Low-High (2)	Low-Low (3)	High-Low (4)	(5)
Average age	High-High	64	30	44	24	162
	Low-High	27	14	17	15	73
	High-Low	5	5	10	7	27
	Low-Low	15	9	35	11	70
		Pearson χ^2 = 20.51 Pr = 0.015				
Age dispersion	High-High	71	20	33	15	139
	Low-High	9	8	18	18	53
	High-Low	5	9	18	6	38
	Low-Low	26	21	37	18	102
		Pearson χ^2 =44.65 Pr = 0.000				
Share of professionals	High-High	27	20	43	19	109
	Low-High	18	4	12	9	43
	High-Low	32	18	36	19	105
	Low-Low	34	16	15	10	75
		Pearson χ^2 = 15.87 Pr = 0.070				
	Total obs.	111	58	106	57	332

Notes: The table reads as follows. The value in row (1) and column (1) indicates 64 positive co-movements toward old-worker concentrations and high-innovation clusters, whereas row (4) and column (1) tell us that we observe 15 regions that move both in the direction of higher innovation clustering and young worker concentrations.

A.5 Calculation of LISA Transition Matrices

In order to compute LISA transition probabilities, we follow a markov chain approach. First, we specify a state probability vector $P_t = [p_{1t}, p_{2t}, p_{3t}, p_{4t}]$ that represents the probability of a region to be in one of the four states (in our case, the four quadrants of the Moran scatterplot) in period t, where $t = 1, 2, ..., 14$ in our case. We then define a 4×4 transition probability matrix, $\mathbf{M} = [m_{ij}]$, showing the likelihood of a region to remain in initial state i or to move from state i in period t to state j in period $t + 1$ during the 14-year period. Transition probabilities are assumed to be time-invariant, that is we assume a homogenous markov chain. Given these assumptions, the state probability vector in period t can be written as $P_t = P_0\mathbf{M}^t$, where P_0 is the initial state vector. In the long-run, the markov chain converges to the steady state vector d.