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DISCUSSION PAPER SERIES

IZA DP No. 17058

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ABSTRACT

Unemployment, Segregation, and the Structure of Cities*

We examine the residential segregation of workers and the unemployed in the 80 largest cities in Germany. Drawing on a large set of geo-referenced data for the period from 2000 until 2015, we are able to study the within-city distribution of unemployment in unprecedented detail. We document a strong and persistent rise in segregation between workers and the unemployed along three dimensions: spatial unevenness, centrality, and localization. First, we show that cities have become spatially less even with respect to the distribution of unemployment. Regarding centrality, we demonstrate that local unemployment rates tend to be highest in downtown areas and decrease quickly with distance from the urban core. This relationship has strengthened over time. We investigate whether a strong reurbanization trend in German cities after 2007 might explain rising unevenness and concentration of unemployment in the center, but find little affirmative evidence. Instead, the strong overall rise of segregation was characterized by a third phenomenon: a trend towards 'localization', i.e., a tendency of workers and the unemployed to sort into increasingly small-scale but internally more homogeneous residential areas.

JEL Classification: J61, R11, R12, R23

Keywords: unemployment, urban labor markets, residential segregation, spatial structure

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1 Introduction

Residential segregation is one of the most pervasive features of the structure of a city. Exclusive high-rise residential areas coexist with neglected neighborhoods, old villa districts and small-scale sprawl in the suburbs. Together, they all shape the character of a city and affect its perception in the eyes of both the passing visitor and the long-time inhabitant. However, while the local population of a city can easily tell the difference between the "good" and the "bad" quarters and has a fine sense for the changes in their residential area, the empirical literature is surprisingly silent when it comes to providing comprehensive analyses of the evolution of city structures and segregation patterns. A large part of the existing literature, which is usually focused on the US, examines the aspect of ethnic segregation (see, e.g., Sethi and Somanathan (2004); Wagmiller (2007); Cutler et al. (2008)). When it comes to socio-economic segregation in Europe, however, most of the research is based on case studies covering only a very limited number of cities, relies on cross-sectional data, or focuses on large administrative areas that do not allow for comparisons between small-scale neighborhoods. With the issue of available and affordable housing pushing to the forefront of the political agenda in recent years, a fresh look into the empirics of segregation is therefore warranted. In addition, understanding the extent and dynamics of segregation in Europe is of major importance for the design of public policies since the local clustering of deprivation and unemployment has been shown to unfold negative social, economic and political external effects.[1]

In this article, we address this gap in the literature by providing an analysis of the extent and dynamics of residential segregation between workers and the unemployed in Germany and relating them to the changing structure of cities. To this end, we draw on large-scale administrative worker and unemployment data as well as on geo-referenced residential addresses and assemble a detailed geographical grid data set for the largest 80 cities in Germany over the period from 2000 to 2015. These data not only allow us to consistently measure the evolution of residential segregation over one and a half decades, but also enables us to look beyond administrative city boundaries and to thereby study city structures and their relation to segregation more comprehensively.

In the first part of this study, we provide descriptive evidence on the extent and evolution of segregation between workers and the unemployed in German cities. To do so, we rely on the Theil Index for measurement both due to its simplicity and composition invariance, which is of particular importance with national or city-wide unemployment rates trending up or down. We show that the level of spatial unevenness has consistently risen throughout the period of study. In addition, we provide evidence that cities differ considerably in the extent to which they are segregated and that the degree of spatial unevenness tends to be lower in larger cities.

In the second part of the paper, we focus on the spatial distribution of workers and the unemployed. In particular, we examine the conventional view which, usually backed by anecdote, points to French banlieues or East German socialist tower blocks

[1] Major dimensions encompass negative effects on health (Kramer and Hogue, 2009), crime and violence (Shihadeh and Flynn, 1996), individual job finding prospects (Bayer et al., 2008; Asquith et al., 2021), and political extremism (Futrell et al., 2018).

to argue that the poor are pushed to the urban fringe in European cities. Our results disprove the common myth that the European city is structurally different in this regard from its US counterpart, where unemployment and poverty are often concentrated in urban centers. Accordingly, we show that the gradient of the local unemployment rate with respect to centrality in German cities is positive, stable with respect to various definitions of the center of a city, and also rising. Furthermore, we present evidence that this positive relationship is a true centrality effect and not simply mediated by local population density, which is generally higher in the city center.

We then investigate changes in city structures and their interaction with patterns of residential segregation. First, we demonstrate that German cities have gone through a phase of both city growth and residential concentration between 2007 and 2015. Regarding the question whether this reurbanization was the main driver behind the rise in segregation, our findings suggest, however, that the inflow of workers into cities had a dampening effect on the degree of spatial unevenness. By estimating Recentered Influence Functions of the Theil Index we make these shifts visible, thus allowing for a deeper look into the changes in city structures and residential segregation patterns.

In the last part of this paper, we address the apparent puzzle emanating from our analysis: if segregation is not driven by large-scale shifts in population density as a consequence of reurbanization, which other mechanisms are at work here? To tackle this question, we propose a simple yet insightful divergence measure that allows us to distinguish between segregation patterns that are of larger geographical scale and those that are smaller-scale and localized. We find that German cities have gone through a phase of localization of segregation with homogeneous neighborhoods becoming smaller and more scattered. These micro-geographic processes have contributed to a higher level of residential segregation in every major city in Germany.

Our article relates to at least three strands of the literature. First, it contributes to the research on socio-economic geographical segregation. This body of work has mostly shown rising levels of segregation both in the US and Europe over the past decades (see, e.g., Glaeser et al. (2008), Watson (2009), Reardon and Bischoff (2011), Quillian and Lagrange (2016) and Musterd et al. (2017) for the US and Farwick (2012), Friedrichs and Triemer (2008) and Helbig and Jähnen (2018) for Germany). Extending the existing evidence, our paper is the first one that is able to study residential segregation for a complete set of large cities in a country with annual and very detailed geo-referenced grid data spanning one and a half decades. We are thus able to precisely document and examine heterogeneous patterns of segregation within cities.

Second, our paper is relevant to the urban economics literature that aims at explaining the distribution of workers and the unemployed within a city (Zenou, 2000; Smith and Zenou, 2003; Wasmer and Zenou, 2006). This literature has been strongly influenced by the empirical work on spatial mismatch in the US (Zenou and Boccard, 2000; Conley and Topa, 2002; Gobillon et al., 2007) but at the same time lacks input from a broader range of institutional backgrounds. Our insights on the relationship between centrality and unemployment in Germany provide evidence on the relative location of workers and the unemployed in a city within the so far under-researched European context.

Third, our paper contributes to the literature on suburbanization and reurbanization. This literature has documented some signs of a renewed densification of core and inner cities in the US (Glaeser and Gottlieb, 2006), Europe (Turok and Mykhnenko, 2007), and Germany (Heider and Siedentop, 2020). There have also been efforts to link suburbanization or reurbanization with trends in residential segregation (see Florida and Mellander (2018) and Miller (2023)). Our paper adds to this literature by providing evidence for an ongoing process of reurbanization and centralization in Germany at a very fine-grained scale, suggesting that this trend might have had a dampening effect on residential segregation in inner cities. Doing so, we connect research in urban economics, urban sociology, and urban planning and highlight new avenues for future research.

The paper is structured as follows: in the next section we outline the data, present the city selection and explain the main employment indicators that will be used throughout the analysis. Section 3 introduces our main measure for overall segregation and provides evidence on the degree and the evolution of spatial unevenness between workers and the unemployed in Germany over time. Drawing on the notion of centrality, Section 4 explores the relative location of workers and the unemployed within cities. In Section 5, we relate changes in the level of segregation to an ongoing process of reurbanization in Germany. Section 6 unites the earlier analyses by examining the scale and structure of segregation in German cities in greater detail. Section 7 concludes.

2 Data and Measurement

2.1 Cities and Grid Cells

We measure the within-city distribution of workers and the unemployed for all cities in Germany with more than 100,000 inhabitants. Table B.1 in the Appendix provides a list of these 80 cities as well as their respective population numbers. The largest city is Berlin with a total population of nearly 3.7 million, the smallest one is Hildesheim with slightly more than 100,000 inhabitants. The average population number is 332,210. As settlement structures typically do not end discontinuously at the administrative border of a city but rather extend into the surrounding hinterland, we extend out city definition by a ring along the outer city borders with a depth of 11 kilometers.[2] Throughout the paper, we refer to the combination of a core city and its hinterland as one 'region'. Figure C.1 in the Appendix illustrates the location and geographical spread of these 80 regions in Germany. Dark blue areas indicate the core cities, light blue rings represent their respective hinterland. As shown in the figure, while the most populous German regions are scattered across the entire country, there is a tendency towards concentration in the industrial belt in the West (*'Ruhrgebiet'*). Each region covers on average an area of 632 square kilometers. We split this area up into grids of 500 x 500 meters. In total, the 80 regions consist of 384,937 grid cells.

[2] For reasons of data parsimony, we had to restrict ourselves to the 80 largest cities in Germany and their respective hinterlands. A ring of 11 kilometers was chosen because this is equal to the median commuting distance in Germany (see Heuermann et al. (2017)). As commutes rarely end at the administrative city border, we are therefore likely to effectively cover the main commuting zones.

Excluding overlaps and, for data privacy reasons, cells with less than five persons in the labor force leaves 133,868 unique cells.[3] These cells comprise an area of 33,467 square kilometers, which is equal to 9.4 percent of the total land area covered by the Federal Republic of Germany (357,386 square kilometers in total). To illustrate the setup and level of detail, Figure C.2 in the Appendix shows the grid structure for Berlin. Together, the city and the hinterland consist of 6,255 grid cells with 47.5 percent of them being located within the city borders (gray cells) and the rest outside (blue cells).

2.2 Worker and Unemployment Data

To study residential segregation in German cities, we draw on a large-scale administrative data set provided by the Institute for Employment Research (IAB). The Integrated Employment Biographies (IEB) are based on German social security records and contain information on all workers, unemployed persons and recipients of social security benefits in Germany on a daily basis.[4] Important for our purpose, the precise geo-coordinates of each worker's place of residence can be added from the geo-referenced address database of the IAB (IEB GEO).[5] Based on these information, we generate an annual panel data set that contains all full-time or part-time employed workers as well as all registered unemployed persons who have their place of residence within one of the 80 regions on June 30th of a given year.[6] Table B.2 in the Appendix shows the number of observations by employment status and year. On average, we observe 20.5 million workers and 3 million unemployed persons which, depending on the year, is equal to a share of 49 to 55 percent of the total labor force in Germany. We merge the grid structure of the 80 regions to these data and calculate the number of workers within each 500 x 500 meter grid cell as the sum of all individuals who have their place of residence within this grid cell on June 30th and are holding a full-time or part-time job within or outside the grid cell. The number of unemployed within a cell is defined as the sum of individuals who reside in a grid cell and are officially registered as unemployed with the Federal Employment Agency on June 30th of a given year. For the rest of this paper, we define the sum of those two groups as the 'labor force'.

2.3 Grid-Cell Specific Unemployment Rates

Based on the number of workers and unemployed in each 500 x 500 meter cell, we calculate the grid-cell specific unemployment rate in the following way. In terms of notation, we refer to one region as r. Each of the regions contains $p = 1, ..., P_r$ grid cells. The number of workers in each grid cell in a given year t is denoted as τ_{prt}^W and the number of unemployed as τ_{prt}^U. As a result, the number of persons in the labor force amounts to $\tau_{prt} = \tau_{prt}^W + \tau_{prt}^U$ in a grid cell and to $N_{rt} = \sum_p \tau_{prt}$ in a region. Based on

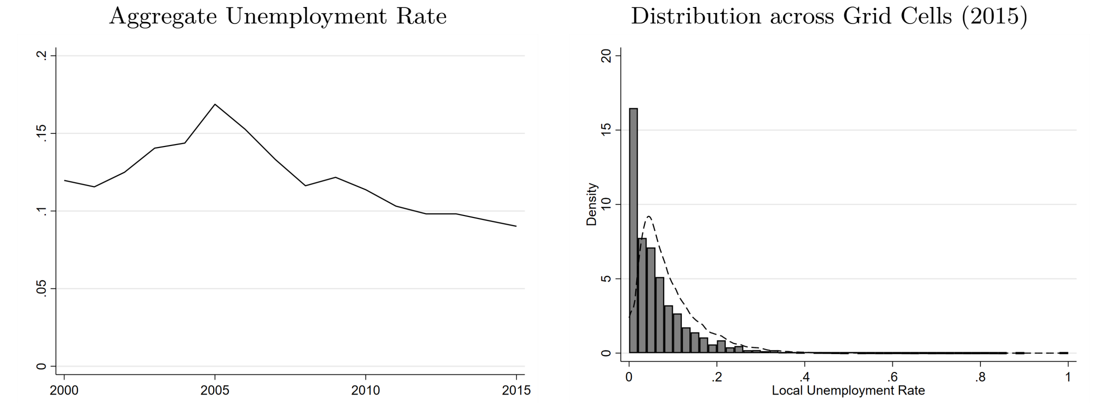
3 'Labor force' refers to the persons contained in our data set as defined in Section 2.2.

4 'Integrierte Erwerbsbiographien', IEB V13.01.00-181010, Nürnberg 2018.

5 'Geocodes von Wohn- und Arbeitsorten der Personen und Betriebe aus IEB V12.00', IEB GEO V01.00.00-201504, Nürnberg 2018; see Ostermann et al. (2022) for a detailed description.

6 Note that marginally employed persons (*'Minijobber'*) are excluded from the analysis.

Figure 1: Unemployment - Evolution & Distribution



Notes: The left panel shows the aggregate unemployment rate between 2000 and 2015 (calculated based on our own data). The right panel shows the distribution of unemployment rates across grid cells (unweighted as bins and weighted by labor force per cell as kernel density). **Source:** Own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

this, the grid-cell specific unemployment rate is calculated as

$$\pi_{prt} = \frac{\tau^U_{prt}}{\tau_{prt}} \tag{1}$$

Figure 1 shows the evolution of the aggregate unemployment rate in our data over the period of observation as well as the distribution of unemployment rates across grid cells.[7] Overall, there is significant heterogeneity over space and time. As shown in the left panel, the unemployment rate rose from 12 to 17 percent between 2000 and 2005 and fell thereafter to around nine percent.[8] In line with these numbers, the right panel shows that the majority of grid cells exhibit a local unemployment rate of less than 20 percent in 2015. One drawback of using grid cells as the unit of observation is that they may cut through local neighborhoods. To address this issue, we also consider spatially smoothed variants of π_{prt} and τ_{prt} (denoted as $\tilde{\pi}_{prt}$ and $\tilde{\tau}_{prt}$) in our analysis. These are calculated as weighted averages over 12 grid cells forming a diamond shape around the center grid (equal to an area of 3 km^2), where the outer grids are assigned about 1/5 of the weight of the center (see Appendix A.2 for details on spatial smoothing).

To provide a first visual impression of the geographical variation of unemployment rates between cells and over time, the left column of Figure C.3 shows the evolution and distribution of unemployment patterns in Berlin. At the turn of the millennium, unemployment rates were substantially higher in the city center than in the outskirts. More specifically, pockets with unemployment rates exceeding 25 percent tended to concentrate predominantly in three parts of the inner city (Spandau, Wedding, Tempelhof).

[7] This aggregate rate is not identical with the official national unemployment rate because, first, it is calculated for the 80 regions only and, second, our data set does not include public servants (*'Beamte'*), marginally employed workers (*'Minijobber'*), self-employed workers (*'Selbständige'*) as well as cross-border out-commuters (*'Grenzpendler'*), who all form part of the total labor force and thereby decrease the official unemployment rate.

[8] The decrease of the unemployment rate after the year 2005 is to some extent the result of a series of major labor market reforms in Germany (*'Hartz Reforms'*). In Appendix A.1, we explain how we have addressed structural breaks in the data that result from the reforms.

With the recession of the first half of the decade, unemployment rates increased in most parts of the city until the year 2006. After that, economic recovery led to falling unemployment rates in most parts of Berlin. At first visual inspection, however, the spatial distribution of unemployment has remained largely stable over time, as has the spatial distribution of labor force density (right column of Figure C.3). In the following sections, we will examine these first descriptive findings in a statistically thorough way and extend them beyond the case of Berlin with the intent to find common trends in the spatial structure of urban unemployment in the 80 largest cities in Germany.

3 The Spatial Distribution of Unemployment

To obtain a general overview of the spatial distribution of unemployment, we study segregation by means of the spatial unevenness of unemployment rates within cities. We introduce the Theil Index as our measure of spatial unevenness in Section 3.1 and then describe the extent and evolution of the unevenness of unemployment in Section 3.2.

3.1 Measuring Spatial Unevenness

The key objective of this section is to consistently measure the degree of spatial unevenness between workers and unemployed persons within each of the 80 regions and to describe and compare its evolution between regions and over time. To do so, we use a region-year specific Theil Index T_{rt}, which is computed as

$$T_{rt} = \frac{1}{N_{rt}} \sum_{p} \tau_{prt} \frac{\pi_{prt}}{\pi_{rt}} \ln(\frac{\pi_{prt}}{\pi_{rt}}). \tag{2}$$

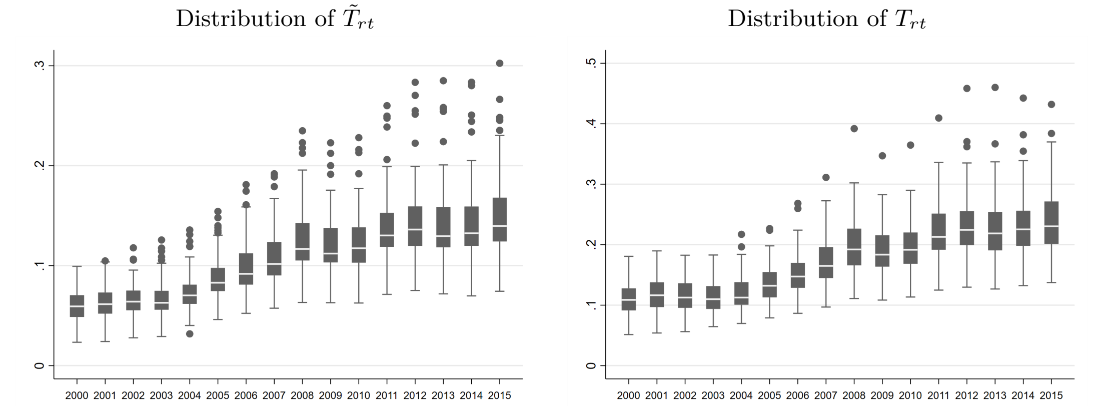
The Theil Index is defined between 0 (even distribution) and $ln(N_{rt})$ (maximum unevenness). It measures the extent to which the cell-specific unemployment rates π_{prt} deviate from the overall unemployment rate π_{rt} in a region in a given year. With a theoretical value of 0, the unemployment rate in each cell equals the region-wide unemployment rate; a value of $ln(N_{rt})$ would arise in situations where all unemployed persons are concentrated in one cell while all employed persons reside in the other cells.[9]

The key advantage of the Theil Index, which in our setting makes it superior to the widely used Dissimilarity Index and the Information Theory Index, lies in its composition invariance, i.e., the value of T_{rt} is unaffected by changes in the overall unemployment rate. This property is of particular importance given the time-series nature of the data conjoint with substantial variations in the macroeconomic environment indicated by Figure 1.[10] In addition to the 'aspatial' Theil Index T_{rt}, we also calculate a spatially smoothed variant $\tilde{T}_{rt}$ to account for the local neighborhood of a cell (see Appendix A.2).

9 More precisely, $T_{rt} = ln(N_{rt})$ if $\tau_{rt}^U = 1$ and $\pi_{prt} = 1$ for exactly one p, i.e., there is only one unemployed person in region r and this person lives alone in cell p.

10 There is a long-standing debate on the correct choice of an indicator, which depends on the nature of the question and the data at hand. We refer the reader to the key contributions by Massey and Denton (1988), Massey et al. (1996), Reardon and O'Sullivan (2004) and Brown and Chung (2006), which also contain summaries of the literature. Note that we have conducted the subsequent analysis also with the Dissimilarity Index and the Information Theory Index defined in Appendix A.3 and refer to the results later in this section.

Figure 2: Spatial Unevenness over Time



Notes: The left panel shows boxplots of the spatially smoothed Theil Indices $\tilde{T}_{rt}$ for the 80 largest cities in Germany (including their hinterland) for the years 2000 to 2015. In the right panel, $\tilde{T}_{rt}$ is replaced by the 'aspatial' Theil Index T_{rt}. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

3.2 Extent and Evolution of Spatial Unevenness

The left panel of Figure 2 shows the distribution of the region-specific spatially smoothed Theil Indices by year from 2000 to 2015. The first key insight from the boxplots is that the distribution of unemployment within the 80 regions has become more uneven over time. Starting from a value of 0.065 in 2000, the median of $\tilde{T}_{rt}$ has more than doubled to 0.14 in 2015. This finding suggests that workers and the unemployed increasingly tend to live in different neighborhoods of a city. Second, the fact that the interquartile range has increased from 0.035 to 0.075 indicates that regions have become more heterogeneous over time with regard to their level of segregation. As a third insight, it is noteworthy that outliers are located only at the top of the distribution. Regions with particularly high levels of spatial unevenness encompass Hildesheim, Ingolstadt, Pforzheim, Bremerhaven, and Kiel.[11] Still, the rise in spatial unevenness is universal: not a single region shows a lower degree of spatial unevenness in 2015 compared to 2000. With an overall increase of 4.5 times the standard deviation of the between-city distribution of the Theil Index in 2000, this shift is of substantial magnitude.

We corroborate and extend these findings in four major ways. First, in order to gain a better understanding of the practical relevance of spatial smoothing, we compare the results obtained for the spatial Theil Index with the ones for the aspatial version. The right panel of Figure 2 shows the distribution of T_{rt} by year. Finding the level of spatial unevenness to be higher without spatial smoothing is in line with intuition as the application of spatial smoothing reduces the differences in unemployment rates between grid cells. At the same time, however, the overall pattern of the distribution looks very similar to the smoothed version. In fact, the median of T_{rt} rises from 0.11 to 0.24 between 2000 and 2015 and the interquartile range increases from 0.35 to 0.7.[12] Overall, these findings are insightful because they show that spatial smoothing changes

[11] A full list of all cities and their respective Theil Index can be found in Table B.3 in the Appendix.
[12] The two outliers in this figure are Wolfsburg and Ingolstadt.

the extent of measured segregation but leaves the general pattern unaltered.[13]

Second, we calculate the spatially weighted versions of the Dissimilarity Index $\tilde{D}_{rt}$ and the Information Theory Index $\tilde{H}_{rt}$ per region and year as two alternative measures of segregation (see Section A.3 in the Appendix for definitions and notation). Figure C.4 in the Appendix provides the boxplots of both indices for each year. It shows that the evolution of $\tilde{D}_{rt}$ and $\tilde{H}_{rt}$ over time is very similar to the one exhibited by the Theil Index. In line with Helbig and Jähnen (2018), who use the Dissimilarity Index to document a rise in social, ethnic and demographic segregation in Germany, we find the same tendency for regions to become more segregated on average as well as more diverse with regard to their respective level of segregation. Outliers are almost exclusively located at the upper end of the distribution and encompass the same regions as with the Theil Index.

Third, we examine the question whether the degree of segregation varies with city size. A comparison of existing studies suggests that the direction of this relation depends on the particular country at hand. For the US, larger cities tend to be more segregated with regard to income, race, and education than smaller ones (Gordon and Monastiriotis, 2006) although part of this relation has been criticized as spurious (Krupka, 2007). Looking at the state of Uttar Pradesh in India, Haque et al. (2018), in contrast, show that segregation by caste is more pronounced in smaller cities than in larger ones. In Figure C.5 in the Appendix, we shed light on this relation for the German case. The left panel shows that the incidence of unemployment rises on average with city size. As indicated in the right panel, this higher unemployment rate does, however, not come with a higher level of spatial unevenness. To the contrary, the most populous of the 80 region actually present themselves as having a more even distribution of unemployment compared to their smaller counterparts.

Finally, we replace the number of unemployed persons in Equation (1) with the number of recipients of social welfare benefits (‘*SGB2/Hartz IV*’). This group is arguably a closer proxy for poverty in Germany since the notion of ‘unemployed persons’ by definition includes high-wage earners who only recently lost their job while at the same time excluding the working poor who receive social benefit transfers. Still, we decided against the benefit recipient rate as our main indicator as it can only be reliably measured after 2006, which would severely truncate our study period. The left panel in Figure C.6 shows the spatially smoothed version of the Theil Index for workers and recipients of social benefit transfers. It provides two main insights. First, rising from an average of 0.145 in the year 2006 to 0.175 in 2015, the evolution of spatial unevenness closely resembles the one between workers and the unemployed. At the same time, the Theil Index is significantly larger compared to the one between workers and the unemployed, suggesting that poverty is distributed even more spatially uneven in German cities than unemployment alone. Overall, these findings show that the US and Germany exhibit

[13] The Theil Index can be decomposed into one part showing the inequality of observations with strictly positive unemployment rates and a correction term $-ln(1-p)$ for cells without unemployment, where p is the share of cells with zeros (see Morrisson and Murtin (2013)). Since the share of grid cells without unemployment more than doubled from 1.4 to 3.2 percent between 2000 and 2015, 14 percent of the overall increase of T_{rt} is due to an increase in the number of such cases. For $\tilde{T}_{rt}$, zeros play only a marginal role as the spatially weighted unemployment rates are rarely exactly zero.

a similar trend towards a rising level of segregation in urban areas (see, e.g., Cutler et al. (2008), Logan et al. (2004), Massey et al. (2009) and Wagmiller (2007)). In the remainder of this paper, we examine how these changes in the level of segregation relate to a shifting spatial structure of unemployment within cities.

4 Unemployment and Centrality

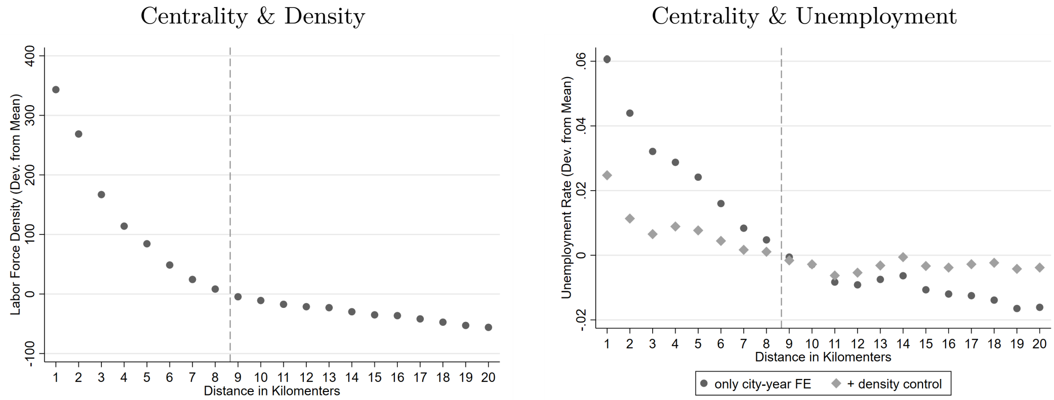
Canonical models in urban economics are ambiguous with regard to their predictions on where workers and the unemployed live in a city. On the one hand, high housing prices in the center may push unemployed people to the urban fringe as they cannot afford the costs of living in the center (Zenou, 2000; Wasmer and Zenou, 2006). Conversely, a concentration of unemployment in the urban centers may result from a preference of the unemployed to be closer to potential jobs (Wasmer and Zenou, 2002) or to be able to use public transportation (Patacchini and Zenou, 2005).

Empirically, the case is unambiguous for the US where unemployment has been shown to be concentrated in the urban centers of major cities (see, e.g., Conley and Topa (2002)). This pattern has been related to the 'spatial mismatch hypothesis', which states that well-paid jobs and well-educated (white) workers have over time moved to the suburbs, leaving black workers in the urban centers behind. Key elements of this theory are a preference of whites to live in the suburbs, racial discrimination in the housing market (Zenou and Boccard, 2000; Brueckner and Zenou, 2003; Hellerstein et al., 2008), distance to jobs (Smith and Zenou, 2003), and a lack of job referral networks (Hellerstein et al., 2014). A large body of literature, which is surveyed by Ihlanfeldt and Sjoquist (1998) and Gobillon et al. (2007), has confirmed the relevance of each of these elements for spatial patterns in the US. As one recent example, Miller (2023) shows that the shift of job opportunities to the suburbs has contributed to the rising level of segregation.

The empirical literature for Europe is, in contrast, of a more recent and fragmented nature with most contributions examining single cities or groups of cities. Existing studies suggest that the opposite pattern prevails in those places that have so far been subject to examination. Gobillon and Selod (2007) and Quillian and Lagrange (2016) show for the French case that in line with common perception unemployment and poverty tend to concentrate in the banlieues, i.e., the outer areas of major cities in France. Andersson and Kährik (2015) provide evidence for a similar pattern in Stockholm.

For Germany, the literature has so far focused mainly on ethnic segregation without addressing the dimension of unemployment and the location thereof. Glitz (2014) argues that a high level of immigrant segregation has prevailed over the last 30 years; Dill et al. (2015) relate this to the discrimination against immigrants in the housing market. Complementing their research, we proceed by examining the spatial structure of unemployment within German cities. More precisely, we shed light on the question where unemployed persons live relative to the center of a city. 'Center' in our analysis is defined by the location of the main train station, which for historical reasons usually is the factual midpoint of a German city. We will conduct robustness checks with alternative definitions of a city center at the end of this section.

Figure 3: Centrality, Density, and Unemployment



Notes: The left panel shows the spatially smoothed labor force density as deviations from the city-specific mean by distance to the city center pooled for the 80 regions and the years 2000 to 2015. The right panel shows the same for the spatially smoothed local unemployment rate. The dashed line represents the average distance from the city center to the border between the city and the hinterland. All models control for city-year fixed effects. "+ density control" indicates that the model also controls for local labor force density. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

4.1 Labor Force Density, Unemployment Rates, and Centrality

In a first step, we examine the density profile of the 80 regions by regressing the spatially smoothed number of persons in the labor force within a grid cell on distance to the center while controlling for city-year fixed effects. The regression equation takes the form

$$\tilde{\tau}_{prt} = \mathbf{\Omega_{pr}}\boldsymbol{\beta} + \mu_{rt} + \varepsilon_{prt} \tag{3}$$

where $\tilde{\tau}_{prt}$ refers to the number of persons in the labor force within a grid cell, $\boldsymbol{\Omega_{pr}}$ is a row vector of dummy variables for each kilometer of distance between a grid cell and the city center, μ_{prt} denotes city-year fixed effects and ε_{prt} is an error term. The coefficients of interest are denoted by the column vector $\boldsymbol{\beta}$, which measures the average deviation of the labor force density from the city-specific mean by distance band. The left panel of Figure 3 shows the results. In line with urban economic theory, labor force density (with regard to place of living) is highest in the center of a city and falls monotonically with distance. This result complements the findings by Krehl (2015) and Heider and Siedentop (2020), who document a similar pattern with regard to the location of jobs.

As a next step, we examine how the local unemployment rate varies with distance to the center. To do so, we regress the cell-specific spatially smoothed unemployment rate $\tilde{\pi}_{prt}$ on dummy variables for each distance band as well as city-year fixed effects:

$$\tilde{\pi}_{prt} = \mathbf{\Omega_{pr}}\boldsymbol{\gamma} + \mu_{rt} + \nu_{prt} \tag{4}$$

In contrast to Equation (3), we now weight the regression by cell size τ_{prt} to account for an uneven distribution of the labor force between grid cells. The coefficients measuring the relationship between centrality and unemployment are denoted by the vector $\boldsymbol{\gamma}$; ν_{prt} is an error term.

The right panel of Figure 3 shows the estimates for $\boldsymbol{\gamma}$. The key insight is that the incidence of unemployment in Germany rises - as in the US - with centrality. More precisely, the unemployment rate in the center is on average six percentage points higher than the city-specific mean. This number falls monotonically with distance, equals the city-specific average at a distance of nine kilometers from the center and ranges below this value for distances beyond this point. To disentangle the relative contribution that centrality and density have on the unemployment-centrality gradient, we estimate a variant of Equation (4) where we additionally control for log labor force density $ln(\tilde{\tau}_{prt})$. As shown by the light gray dotted line, the conditional unemployment rate in the center falls by about 50 percent in size but still remains about 3 percentage points above the city average. This finding confirms the notion that high unemployment rates in the center are indeed partly driven by location and not by density alone. Overall, these results stand in stark contrast to the findings for other European cities, where unemployment is predominantly a phenomenon of the urban fringe.

We corroborate the robustness of these results in two ways. First, we complement the analysis by exchanging the number of unemployed with the number of social welfare recipients. The left panel in Figure C.7 in the Appendix shows that the share of persons depending on public assistance is also highest in the center of a city and decreases monotonically with distance. This concentration of poverty in the urban centers is even more pronounced than with regard to unemployment. As a second extension, we use the geographic midpoint and the population-weighted center as alternative definitions of the city center. Figure C.8 shows that the results are stable for the population-weighted center while the geographic midpoint in turn seems to miss the true center of a city.

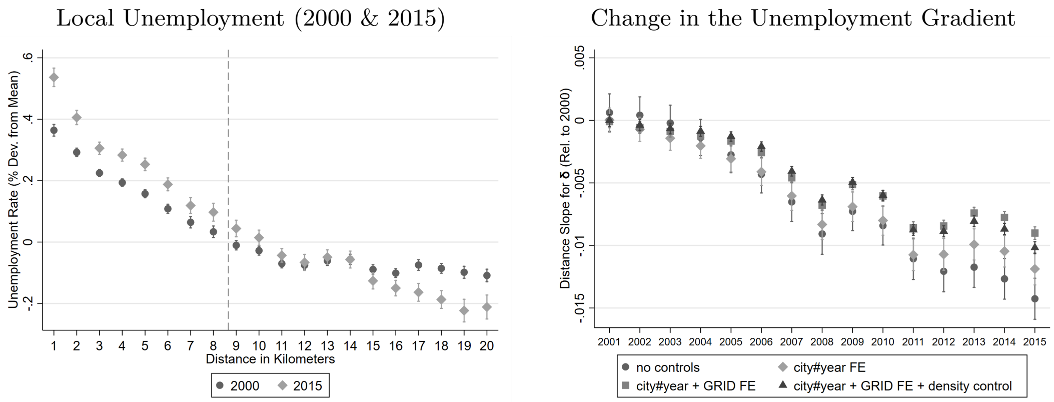
In the remainder of this section, we examine how the unemployment-centrality gradient has evolved over the period of observation. To do so, we alter Equation (4) in two ways. First, we substitute $\boldsymbol{\Omega_{pr}}$ by $\boldsymbol{\Theta_{prt}}$, which is a vector of year-specific dummies for all one-kilometer distance bands with the corresponding coefficient vector $\boldsymbol{\delta}$. Second, we estimate the relationship using the Poisson model

$$\tilde{\pi}_{prt} \sim \text{Poisson}\left(\exp\left(\mathbf{\Theta_{prt}}\boldsymbol{\delta} + \mu_{rt}\right)\right). \tag{5}$$

This model effectively transforms the y-axis in Figure 3 to a log-scale. As a result, variations in city-wide unemployment rates driven by the business cycle will lead to parallel shifts in the unemployment-centrality relationship without affecting its slope. The coefficients of $\boldsymbol{\delta}$ therefore measure unbiased changes in the centrality gradient. The left panel of Figure 4 provides the results from the estimation for the years 2000 and 2015. It shows that the unemployment-centrality gradient has become steeper over the period of observation, suggesting that city centers and the hinterland have become even more different in terms of their local incidence of unemployment.[14] To better understand the size and timing of this change, we estimate the linear slope parameter for every year and relate it to the initial slope of the gradient for the year 2000.

[14] As a robustness check, the right panel of Figure C.7 demonstrates that the centrality of poverty (as measured by the share of social welfare recipients per grid cell) also increased over time, albeit to a lesser degree than for the unemployed.

Figure 4: Unemployment and Centrality over Time



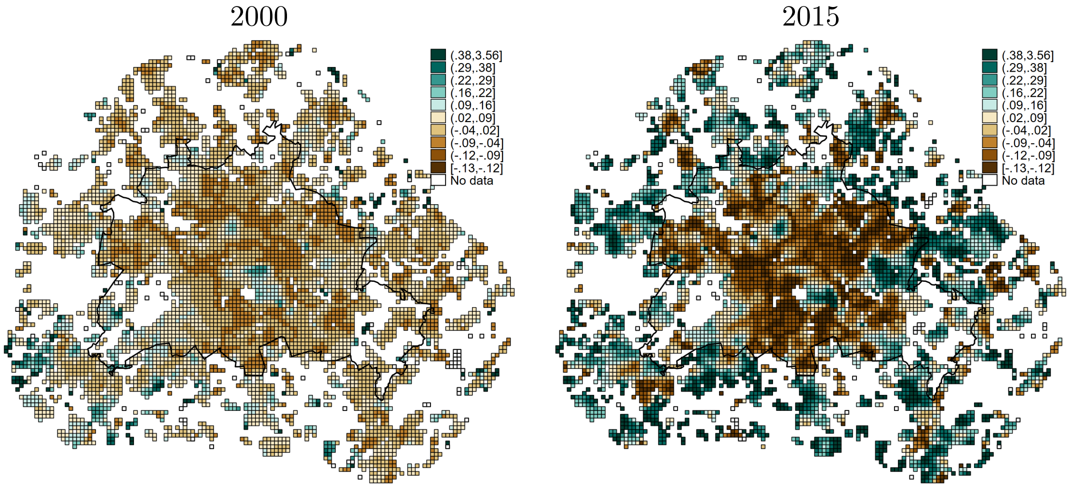
Notes: The left panel shows the average local unemployment rate as percentage deviation from the city-specific mean in 2000 and 2015 by distance to the city center pooled for the 80 regions and controlling for city-year fixed effects. The right panel shows the change in the gradient between the local unemployment rate and distance to the center for the year 2015 relative to the year 2000. It contains model variants (i) without further controls, (ii) including city-year fixed effects, (iii) including grid-cell specific and city-year fixed effects and (iv) both sets of fixed effects and adding local labor force density as a control. The dashed line represents the average distance from the city center to the border between the city and the hinterland. For details on the correction of a structural break in the right panel, see Appendix A.1.
Sources: own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

As shown in the right panel, the unemployment-centrality slope parameter gradually increased in absolute value by about 0.01 until 2015 in our most comprehensive model, which contains city-year and grid-cell fixed effects as well as labor force density as controls. In the year 2000, the slope of the gradient was about -0.02, suggesting that an additional kilometer of distance to the city center was associated with a reduction of the unemployment rate by 0.02 percentage points (which is equal to three percent). Until 2015, this slope has risen to -0.03, which means that the unemployment rate fell on average by 0.03 percentage points (or 3.5 percent) with each additional kilometer from the city center. The following example illustrates the magnitude of the effect from this rotation over the radius of a city: pooled over all years and cities, the average unemployment rate in the center was equal to around 17 percent over the period of study. A slope of -0.02 prevailing in 2000 would imply an unemployment rate of approximately 11 percent at a distance of 20 kilometers from the city center and, hence, a difference of 6 percentage points. With a steeper gradient of -0.03, this difference has risen to 8 percentage points in 2015 (a fixed value of 17 percent in the center and a value of 9 percent at a distance of 20 kilometers from the center).

4.2 Spatial Unevenness and Centrality

To gain a deeper insight into the changing nature of segregation, we proceed by asking whether the rise in spatial unevenness documented in Section 3.2 is mainly driven by the core or the periphery of a city. From a statistical point of view, we aim to measure the contribution of different areas within a city to the overall spatial unevenness of unemployment rates. We address this relation by means of Influence Functions (see Cowell and Flachaire (2007) and Rios-Avila (2020)) where we identify the year-specific

Figure 5: Contribution to Overall Spatial Unevenness - The Case of Berlin



Notes: The figure shows the cell-specific contributions to the overall level of spatial unevenness in Berlin (identified by means of Influence Functions) for the years 2000 (left) and 2015 (right). Brown shades represent below average contributions, green shades above average contributions. Grid cells with less than five persons per cell had to be excluded (white areas). Quantile boundaries are fixed based on the 2015 distribution. **Source:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504). **Layers:** © GeoBasis-DE / BKG 2017.

contribution of each grid cell to the overall Theil Index of a city. Denoting $z_{prt} = \pi_{prt} \ln(\pi_{prt})$ and $v_{rt} = \sum_p (\pi_{prt} \ln \pi_{prt})$, the Influence Function is defined as (see Appendix A.4 for further details)

$$IF(\pi_{prt}; T_{rt}) = \frac{1}{\pi_{rt}} \cdot [z_{prt} - v_{rt}] - \frac{v_{rt} + \pi_{rt}}{\pi_{rt}^2} \cdot [z_{prt} - \pi_{rt}]. \tag{6}$$

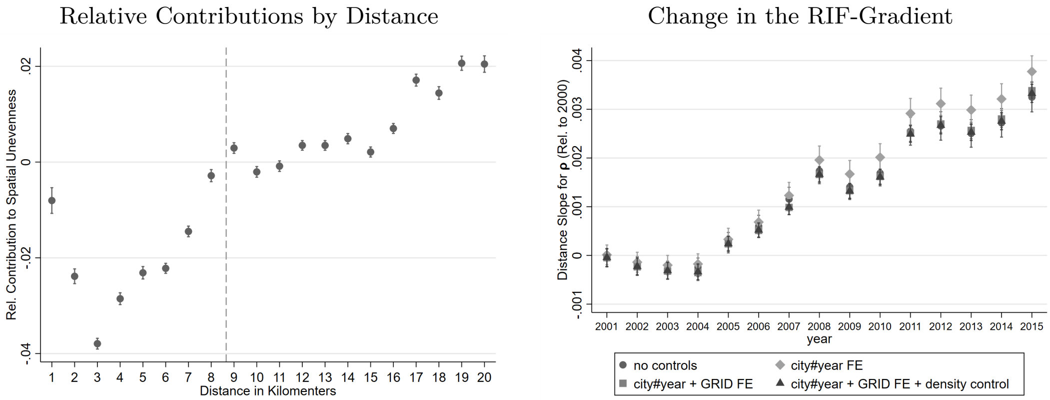
Figure 5 provides a visual impression of the distribution of these relative contributions for the greater Berlin area. Brown shades indicate a below-average contribution of a cell while green shaded cells contribute above average to the overall level of spatial unevenness in Berlin. To allow for a comparison over time, we fix the quantile boundaries for the map based on the distribution of contributions in 2015 (right panel) and then also apply them for the year 2000 (left panel). Two patterns can be identified from the figure: first, grid cells in the center exhibit a lower relative contribution than cells in the periphery. Second, this difference has intensified over the period of observation with a rising gradient from the core to the periphery.

In order to examine whether this spatial pattern holds on average for all 80 regions in our data set, we follow the approach by Firpo et al. (2009, 2018) and regress the Recentered Influence Function (RIF) of a cell, which is defined as the year-specific value of the Influence Function of a grid cell plus the city-year specific Theil Index, on a vector of distance dummies $\boldsymbol{\Omega_{pr}}$ as well as on city-year fixed effects μ_{rt}

$$RIF(\tilde{\pi}_{prt}) = \boldsymbol{\Omega}_{\mathbf{pr}} \boldsymbol{\rho} + \mu_{rt} + \upsilon_{prt}. \tag{7}$$

The left panel of Figure 6 shows the estimates for $\boldsymbol{\rho}$, which measure the average contribution of cells within a distance band to the overall level of spatial unevenness

Figure 6: Contributions to Spatial Unevenness by Distance and over Time



Notes: The left panel shows the relative contribution of grid cells to the city-specific spatial unevenness of the distribution of workers and unemployed by distance band. Estimates are pooled for all years and regions and control for city-year fixed effects. The right panel shows the gradient between this relative contribution and distance to the center relative to the gradient in 2000. It contains model variants (i) without further controls, (ii) including city-year fixed effects, (iii) including city-year and grid-cell specific fixed effects and (iv) additionally controlling for local labor force density. The dashed line represents the average distance from the city center to the border between the city and the hinterland. **Source:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

relative to the city-year specific average. Consistent with the case of Berlin, the relative contribution of a cell rises, with the exception of the city center, on average with distance to the center. Similar to Section 4.1 (Figure 4, right panel), we proceed by examining how the relation between the relative contribution to spatial unevenness and centrality has evolved over time. To do so, we estimate a variant of Equation (5) with the year-cell specific value of the Recentered Influence Function, $RIF(\tilde{\pi}_{prt})$, as the dependent variable. The right panel of Figure 6 shows that the positive slope depicted in the left panel has become steeper over time. In other words, the relative importance of the periphery for the level of segregation has increased over time. This finding is robust to different combinations of fixed effects as well as labor force density as controls.

Overall, the findings from this section can be summarized as follows: first, our results reveal a surprising similarity between cities in Germany and the US with regard to their socio-geographic structure inasmuch as unemployment and poverty tend to be concentrated in the inner cities. This insight holds for different indicators as well as for various definitions of a city center. Second, our estimates of the slope of the centrality-unemployment gradient show that the difference in the incidence of unemployment between the city center and the hinterland has increased over the period from 2000 until 2015. Third, there is no evidence that downtown areas are the main drivers of segregation within a city. To the contrary, peripheral areas in the hinterland contribute more than proportionally to the overall spatial unevenness of a city with this tendency increasing over time.[15] In light of these findings, the key question is: what is the driving and uniting force behind these trends? One explanation that comes to mind is a potential reurbanization of Germany cities. We examine this notion in the next section.

[15] To show that these trends extend beyond our particular definition of unemployment, Figure C.10 in the Appendix repeats the analysis for benefit recipients. The results are broadly similar.

5 Reurbanization and its Relation to Segregation

5.1 (Re)Urbanization in Germany

In the US, the last three decades have witnessed a 'resurgence of cities' (Glaeser and Gottlieb, 2006) with rising population numbers in urban areas. According to the United States Census Bureau (2022), American cities have grown by 6.4 percent between 2010 and 2020. Much of this process can be explained by city centers having become places of attraction in the newly perceived 'consumer city' (Glaeser et al., 2001) with in particular young and highly-qualified workers increasingly seeking to live in the urban center rather than in the suburbs (Siedentop et al., 2018; Couture and Handbury, 2020).

Since the turn of the century, a similar trend towards reurbanization can also be observed for Germany. Based on data for the 43 largest city regions in Germany, Heider and Siedentop (2020) provide evidence for a concentration of jobs and employment in urban areas (see Brombach et al. (2017) for similar results). We complement their research by examining whether processes of reurbanization can also be observed with regard to places of living. To do so, we differentiate between two dynamics that may underlie this trend. One is an overall increase in urban density ('city growth'). The other is a potential shift of the labor force towards the urban center ('centralization').

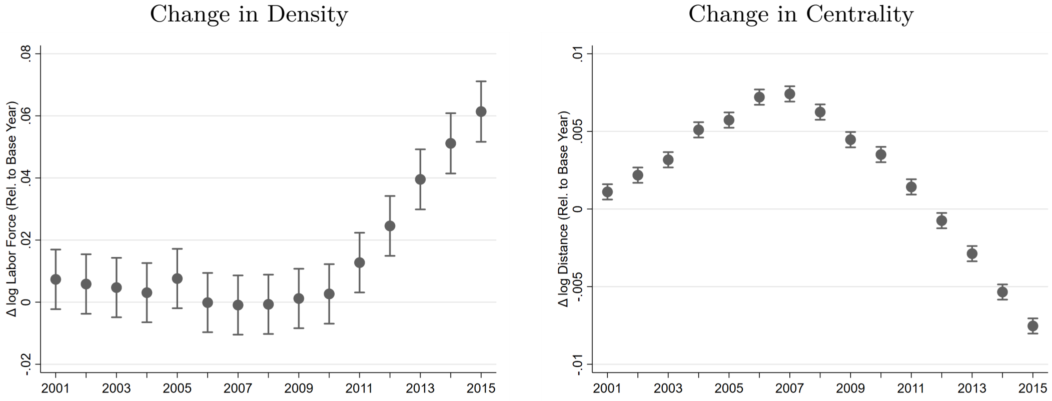
Descriptive evidence from our data set on the labor force shows that, on aggregate, the number of workers and unemployed persons who live in one of the 80 largest cities in Germany or their respective hinterland has grown by five percent from 23.3 to 24.5 million between 2000 and 2015.[16] Consistently, nearly 75 percent of the cities (58 out of 80) followed a positive growth trajectory.[17] At the same time, the share of the labor force living within the urban centers of the 80 regions (delineated by the administrative border of the core cities as opposed to their hinterlands) increased by one percentage point from 46.2 percent in the year 2000 to 47.2 percent in 2015.

To shed light on the timing of both dimensions of reurbanization, the left panel of Figure 7 plots the change in the average labor force density per grid cell relative to the year 2000. The right panel illustrates the percentage change in the average distance of the residential labor force from the city center by year (also relative to 2000). It turns out that after a phase of stagnation in the first half of the study period, the labor force density in the 80 cities started to increase substantially from 2009 onward. Parallel to this growth in city size, the average distance between each person's place of residence and the city center was rising until 2007 ('suburbanization') and falling thereafter ('centralization'). Between 2007 and 2015, the average distance to the city center decreased on average by about 1.5 percent, which amounts to approximately 6

[16] The growth in labor force is slightly higher than the overall population growth since it also captures people entering the labor force from inactivity or marginal employment as a result of the strong labor market. As an example, the labor force in Berlin increased by 8.6 percent between 2010 and 2015 according to our concept of measurement while the overall population only rose by 7.5 percent between 2011 and 2016 (Amt für Statistik Berlin Brandenburg, 2023).

[17] In Table B.1 in the Appendix, the 58 cities which saw an increase in the labor force are marked with an asterisk (*). The 22 shrinking regions encompass mainly cities in the Ruhr-area (*'Ruhrgebiet'*) which have undergone a process of substantial deindustrialization (see Hennig (2019) for similar results) and cities in East Germany, where most regions are subject to a continued out-migration to Western Germany, in particular of young and skilled workers (see, e.g., Heider (2019)).

Figure 7: Suburbanization and Reurbanization



Notes: The left panel shows the percentage change in average labor force density per grid cell relative to the year 2000. The right panel shows the percentage change in the average distance of the labor force from the city center. Both figures are pooled over all 80 regions while controlling for city-specific fixed effects to identify only within-city variation. For details on the correction of a structural break in 2005, see Appendix A.1. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

percent of the standard deviation of the distribution of average distances in 2000.[18] Overall, these results suggest that the inflow of labor force that most cities witnessed during the second half of the period of observation was predominantly targeted at the urban centers rather than at the surrounding areas. In the next section, we relate these developments to changes in the spatial distribution of workers and the unemployed within the 80 regions.

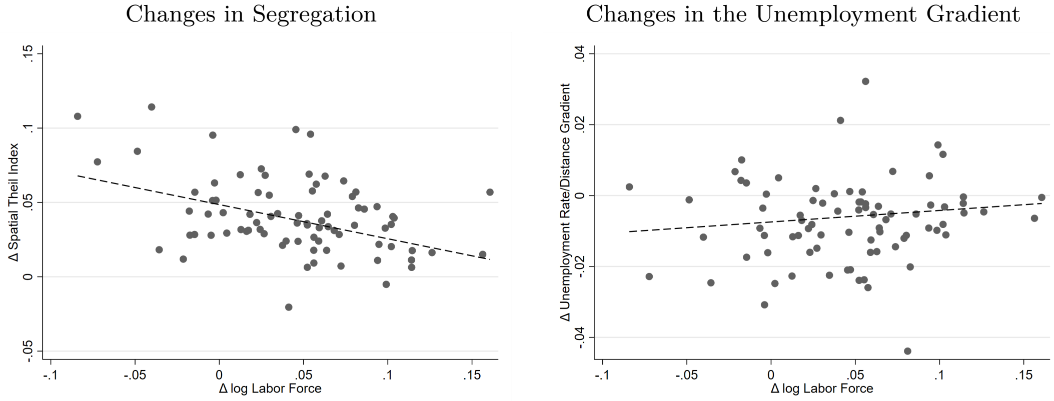
5.2 Reurbanization as a Driver of Segregation?

Given the trend towards a rising residential segregation of workers and the unemployed as well as a tendency of cities to reurbanize after 2007, an obvious question to ask is whether these two developments might be interrelated. One explanation that comes to mind is that the process of reurbanization has contributed to the rise in segregation: as the 'urban renaissance' attracted more and more workers to the inner cities, they bid up housing prices and pushed the unemployed and recipients of welfare benefits either to the periphery or to less popular neighborhoods, which in turn resulted in a higher level of residential segregation. This narrative appears intuitively plausible as it links city growth to a tightening housing markets and the process of gentrification. In order to address this notion, we examine on regional as well as on grid cell level whether the rise in segregation across German cities can be related to an increase in labor force density.

With regard to the regional level, the left panel of Figure 8 visualizes the relation between a change in the city-specific Theil Index and the growth of the labor force in a city for the years from 2007 to 2015, i.e., the period when reurbanization was gaining momentum. The relationship is significantly negative, suggesting that regions that grew stronger with regard to their labor force were at the same time those that saw a more

[18] As shown in Figure C.11 in the Appendix, centralization was most pronounced at close distance to the city center suggesting that the process of reurbanization was mainly directed at the urban core.

Figure 8: City Growth and Spatial Unevenness at the City Level



Notes: The figure relates city growth between 2007 and 2015 to (i) changes in the Theil Index during the same period (left panel) and (ii) changes in the unemployment/distance gradient also between 2007 and 2015 (right panel). Each dot represents one region; city-size weights are used in the estimation. **Source:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

moderate rise in segregation. This result stands in surprising contrast to the argument that reurbanization may be a driving force behind the rise in spatial unevenness. A closely related question is whether the inflow of workforce has altered the distribution of unemployment within a city. We address this notion in the right panel of Figure 8, where we relate the average rise in the unemployment-centrality gradient documented in Section 4.1 to changes in the labor force. Overall, the mildly positive slope corroborates the finding that growing regions saw on average a less steep increase in segregation.

We triangulate these results on grid cell level by drawing on the Recentered Influence Functions introduced in Section 4.2. We now use the cell-specific value of the RIF, which measures the relative contribution of each grid cell to the overall level of segregation in a city, as dependent variable and estimate a variant of Equation (7) that contains labor force density $\tilde{\tau}_{prt}$ as the main explanatory variable while controlling for city-year specific and cell-specific fixed effects μ_{rt} and ψ_p

$$RIF(\tilde{\pi}_{prt}) = \theta\tilde{\tau}_{prt} + \mu_{rt} + \psi_p + \iota_{prt}. \tag{8}$$

Table 1 provides the results on the coefficient of interest θ from different specifications of Equation (8). The first column, which contains no controls, shows that the contribution of a cell to the overall level of spatial unevenness tends to be lower in areas with a high labor force density. This result is in line with the finding from Figure 6 that more central and, hence, more densely populated areas contribute less to the overall level of segregation in a city. This relationship holds when we control for city-year specific characteristics in column (2). The key finding is, however, contained in column (3), where we add grid-cell fixed effects. Note that the relationship between the grid-cell specific contribution to overall segregation and labor force density is now identified solely from within-grid changes in labor force density. The significantly negative coefficient of labor force density suggests that an influx of workforce into grid cells correlates with a reduction in the overall level of segregation in a region. Since these inflows have been

Table 1: Contribution of Local Density to Spatial Unevenness

	(1)	(2)	(3)
$\ln(\tilde{\tau}_{prt})$	-0.0349	-0.0392	-0.0178
	(0.000)**	(0.000)**	(0.001)**
Constant	0.275	0.299	0.182
	(0.001)**	(0.001)**	(0.010)**
Controls	No Controls	City-Year FE	All FE
N	1,563,655	1,563,655	1,561,214
R^2	0.070	0.161	0.773

Notes: The table shows the results from regressing the grid-cell specific values of the Recentered Influence Functions (RIFs) on log labor force density per grid cell. Regressions are pooled for the 80 regions and the years 2000 to 2015. 'All FE' refers to city-year and cell-specific fixed effects. Heteroscedasticity-robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

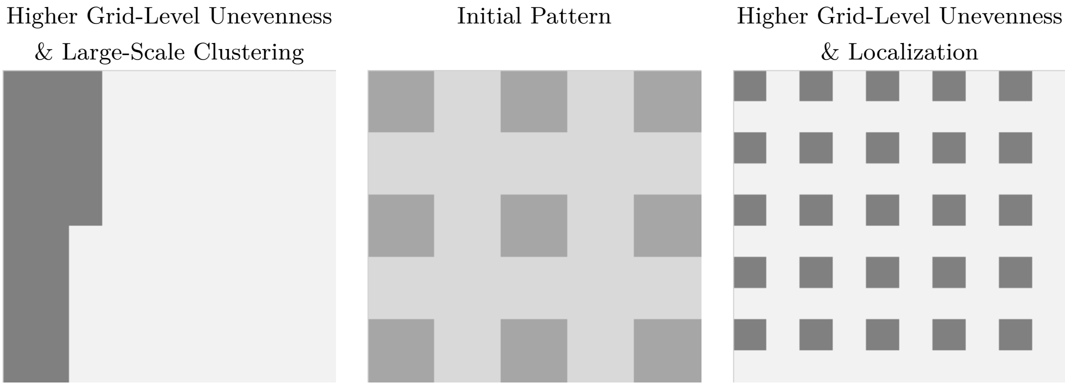
targeted mainly at the inner cities (see Section 5.1), this result supports the notion that re-urbanization may have had a dampening effect on the level of segregation in a region.

Taken together, the findings from this section can be summarized as follows: German regions have undergone a process of reurbanization after 2007 with significant inflows of persons into agglomerated regions as well as a shift of the labor force towards the city center. There is, however, no evidence that these large-scale shifts are a driving force behind the increase in segregation between workers and the unemployed that we have documented in Section 3.2. If anything, it rather seems that the process of reurbanization is reducing the extent to which a region is segregated. In consequence, if the rise in segregation is not driven by superordinate and large-scale shifts in population, it might be the case that more subtle processes are at work.

6 Localization: The Changing Nature of Segregation

Massey et al. (2009) show for the US that the spatial scale of racial segregation has shifted from a macro-level city-wide phenomenon to a more small-scale pattern where segregation takes place between single neighborhoods. For several reasons one may hypothesize that a similar shift in the structure of segregation has also taken place in Germany. First, due to historically low interest rates in the capital market, large urban development projects have come to shape German cities over the last decade. With a soaring demand for urban housing and the resulting rise in real estate prices, such construction activities have often taken place in areas which in the past were not profitable to develop like, e.g., deprived areas or former industrial estates. At the same time, restrictions in urban development emanating from different regulations, e.g., tenant protection or preservation orders, as well as resistance of residents against large-scale investment projects have inhibited the development of certain blocks or single houses, leading to a patchy and heterogeneous structure of urban renewal (see Altrock (2022) for a comprehensive overview). Third, the local availability of amenities as well as access to public transportation have played an increasing role in determining the attractiveness

Figure 9: Segregation at Different Scales



Notes: The figure shows two scenarios where different shifts in the patterns of local unemployment would both yield a higher measured level of spatial unevenness. The Localization Index L_{rt} unveils the respective nature of these shifts by falling in value with a shift from the middle to the left and rising with a shift to the right. **Source:** own representation.

of a neighborhood (Glaeser and Gottlieb, 2006). Together, these forces may have contributed to the formation of a more small-scale pattern of segregation where high and low levels of unemployment coexist in close proximity to each other.

6.1 Measuring Localization

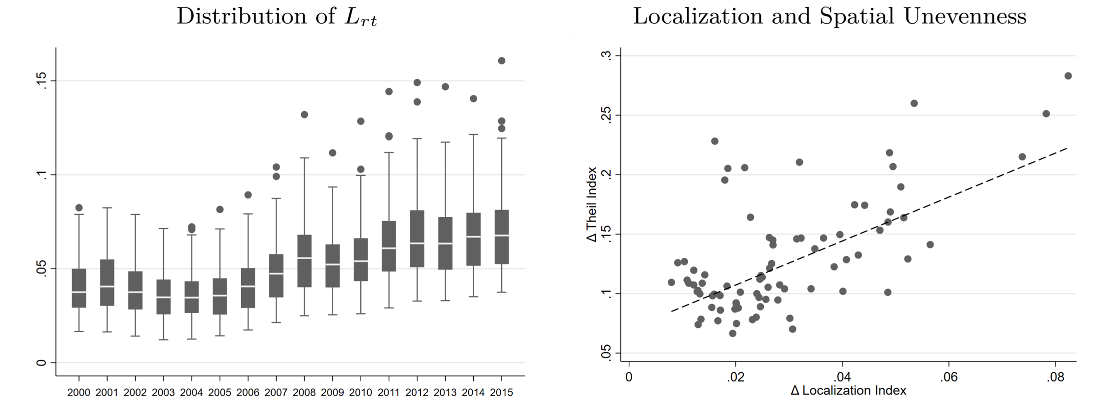
Figure 9 illustrates how a general rise in segregation between workers and the unemployed may be grounded in very different processes on the local level. In all three panels, darker areas indicate a higher local unemployment rate. A shift from the scenario in the middle to the one on the left implies that unemployment gets more concentrated in one part of the city. A shift to the right yields, in contrast, a more dispersed pattern of unemployment. While the spatially weighted Theil Index $\tilde{T}_{rt}$ explicitly takes the local neighborhood of a grid cell into account, it is (like many other spatially weighted segregation indices) not well suited to measure such changes in the structure of segregation as it would indicate a rise in spatial unevenness for both cases, obscuring the fact that the nature of the shift is very different.

To examine whether the spatial scale of segregation has indeed changed in German cities, we construct an entropy-based Localization Index L_{rt}, which is inspired by Mori et al. (2005) and Roberto (2016). Effectively, the index is a version of the Theil Index defined in Equation (2) where the city-wide average unemployment rate in the logarithmic term is exchanged for the locally weighted unemployment rate $\tilde{\pi}_{prt}$

$$L_{rt} = \frac{1}{N} \sum_{p} \tau_{prt} \frac{\pi_{prt}}{\pi_{rt}} \ln\left(\frac{\pi_{prt}}{\tilde{\pi}_{prt}}\right). \tag{9}$$

The key idea of this index is to exploit the deviation between the spatially weighted and the unweighted unemployment rate per cell, $\tilde{\pi}_{prt}$ and π_{prt}. Figure C.9 illustrates the intuition. The setup in the left panel is such that workers and unemployed persons are living in different parts of the city ('large-scale clustering'), while in the right panel high-unemployment and low-unemployment neighborhoods are dispersed over the city

Figure 10: Localization over Time



Notes: The left panel shows boxplots of the Localization Indices L_{rt} for the 80 largest cities in Germany (including their hinterland) for the years 2000 to 2015. The right panel shows the between-city correlation of changes in the Localization Index L_{rt} and in the Theil Index T_{rt} (both measured as long differences from 2000 to 2015). **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

area ('localization'). In consequence, while the difference between $\tilde{\pi}_{prt}$ and π_{prt} will be low for most parts of the city shown in the left panel (except for the boundary areas between the clusters), there will be considerably more divergence between $\tilde{\pi}_{prt}$ and π_{prt} in the more localized city shown in the right panel. As a result, L_{rt} will rise in value with a shift from a large-scale clustering towards a small-scale pattern of localization. With regard to Figure 9, the Localization Index is thus able to disentangle a change in the overall pattern of segregation from an overall rise in segregation.[19]

6.2 Extent and Evolution of Localization

We calculate the Localization Index for each of the 80 regions per year. The left panel of Figure 10 shows the annual distribution of the region-specific L_{rt} for the years from 2000 to 2015. Overall, the degree of localization has remained largely stable with a median value of 0.04 until about 2005 and started to increase thereafter up to a value of 0.07 in 2015. Importantly, as it was the case with spatial unevenness, this rise in the degree of localization was universal for all 80 regions. Appendix B.4 lists the level and evolution of the Localization Index for each region. Over the period of 15 years, not a single one of them defied the trend towards a more small-scale nature of segregation. In fact, the median increase in localization amounted to nearly 2.5 times the standard deviation of the between-city distribution of the Localization Index in 2000. Even for the region with the weakest increase, Augsburg (+0.008), this change would have been enough to elevate it from its original 19^{th} rank in the between-city distribution in 2000 to the 13^{th} rank.

Since this trend despite its ubiquity does not need to be of the same magnitude for each region, we differentiate our results by region type. To do so, we regress the Localization Index on a time trend for different groups of cities. Table 2 shows that the

[19] The Localization Index operates along the spatial exposure/isolation axis as suggested by Reardon and O'Sullivan (2004). It measures, however, the divergence between local neighborhoods rather than the exposure/isolation of individuals.

Table 2: Localization by Region Type

Regions	All	Labor Force Growth Low	Labor Force Growth High	Avg. Income Growth Low	Avg. Income Growth High
	(1)	(2)	(3)	(4)	(6)
Trend	0.0021	0.0017	0.0023	0.0017	0.0027
	(0.0001)**	(0.0001)**	(0.0002)**	(0.0001)**	(0.0002)**
Constant	0.0295	0.0261	0.0331	0.0280	0.0325
	(0.0008)**	(0.0008)**	(0.0016)**	(0.0010)**	(0.0012)**
Cities	80	40	40	40	40
N	1280	640	640	640	640
R^2	0.260	0.275	0.296	0.266	0.328

Regions	Unemployment Growth Low	Unemployment Growth High	Part of Germany West	Part of Germany East	Part of City Core	Part of City Hinterland
	(7)	(8)	(9)	(10)	(11)	(12)
Trend	0.0028	0.0017	0.0020	0.0026	-0.0068	0.0070
	(0.0003)	(0.0002)**	(0.0001)**	(0.0003)**	(0.0011)**	(0.0010)**
Constant	0.0294	0.0296	0.0319	0.0129	-0.0895	0.0896
	(0.0021)	(0.0016)**	(0.0009)**	(0.0019)**	(0.0085)**	(0.0070)**
Cities	40	40	40	40	80	80
N	640	640	640	640	1280	1280
R^2	0.287	0.287	0.250	0.530	0.034	0.040

Notes: The table provides the results from regressing the region-year specific Localization Index L_{rt} on a linear time trend for subgroups of cities. 'Low' and 'High' refers to regions with either below- or above-median (i) growth rates of the labor force, (ii) growth rates of average household incomes, and (iii) growth rates of unemployment rates. Columns (11) and (12) use average RIFs for the Localization Index (see Appendix A.4). Heteroscedasticity-robust standard errors in parentheses; * $p < 0.05$, ** $p < 0.01$.
Sources: own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504); household incomes are obtained from the Bundesinstitut für Bau-, Stadt- und Raumforschung (2024).

shift towards a more small-scale pattern of segregation was stronger in cities that grew more rapidly (column 3), had higher increases in household incomes (column 6) and stronger reductions in unemployment (column 7). Taken together, these results suggest that the move towards more small-scale patterns of segregation has been particularly pronounced in economically successful cities.

At the same time, it is noteworthy that the rise in localization was not driven by the core cities but by their hinterlands (see the results in columns (11) and (12)). In fact, the constant term of the regression corroborates the notion that the hinterland has always contributed more strongly to localization than the urban core. As such, columns (11) and (12) provide a variant of the centrality analysis in Section 4, which has shown that grid cells in the periphery carry a greater weight with regard to the overall level of segregation than the center. Figure C.12 in the Appendix provides a graphical illustration of these shifts by plotting changes in unemployment rates and grid-cell specific contributions to localization for the three biggest German cities: Berlin, Hamburg and Munich.[20] In line with the results from the regressions, the figure demonstrates that localization was more strongly driven by the periphery where unemployment rates also fell the most.

[20] Details on the computation of the grid-cell specific contributions to the Localization Index by means of Recentered Influence Functions (RIFs) are provided in Appendix A.4.

As a last step, the right panel of Figure 10 relates changes in the Theil Index to changes in the Localization Index. In shows that a close positive correlation prevails between both dimensions, suggesting that those cities that became more spatially uneven over time are also the ones that saw the greatest shifts towards a more localized pattern of segregation. While not causal in nature, these results support the notion that the overall rise in the *level of segregation* within German cities can at least partly be related to changes in the *nature of segregation*. Consequently, any conclusive explanation for the rise in segregation in Germany and other countries will have to look beyond between-city heterogeneity and also take changing patterns of the phenomenon into account.

7 Summary and Conclusion

In this paper, we have examined the residential segregation of workers and the unemployed in Germany between 2000 and 2015. Drawing on a large and novel geo-referenced data set, we have provided insight into the socio-spatial structure of the 80 largest German cities and their respective hinterland in unprecedented detail.

As our first main result, we find that the degree of spatial segregation between workers and the unemployed has risen substantially over the period of observation along several dimensions. This finding not only holds for unemployment but also for more general indicators of poverty like the share of welfare benefit recipients. Our second main result relates to the internal socio-economic structure of cities. We find that unemployment and welfare dependency are concentrated predominantly in the urban centers. In fact, there is an economically significant negative gradient between local unemployment rates and the distance of a residential location to the city center. This relationship is for most parts a true centrality effect and not simply mediated by local population density. From 2000 to 2015, this pattern became even more pronounced. In this regard, our results point to a structural similarity between Germany and the US, where the concentration of unemployment and poverty is also mainly a downtown phenomenon. Third, we show that German cities entered a phase of reurbanization after 2007. While cities not only grew with regard to their labor force during this period, there was also a shift of the residential distribution towards the city centers. As a result, cities in Germany became spatially more concentrated. At the same time, however, we find no evidence for the process of reurbanization to be a major driver towards a rising level of socio-economic segregation. The main shift in the spatial structure of unemployment was rather marked by a pronounced and pervasive trend towards localization, i.e., a tendency of workers and the unemployed to sort into smaller-scale but internally more homogeneous residential areas. Notably, this trend has affected (without exception) every major city in Germany.

It is in particular this last result that calls for a reassessment of the nature of socio-economic segregation in Germany. Overall, unemployment and deprivation seem to be increasingly less confined to large and clearly identifiable areas. Rather, unemployment has become more dispersed and at the same time more concentrated within a larger number of small-scale neighborhoods. While these dynamics are neither 'good' nor 'bad' in a normative sense, they require a new spatial focus of social and labor market policies as targeting only the notoriously ‘problematic’ districts of a city seems to increasingly miss the point.

We see a number of exciting avenues for future research based on the findings presented in this paper. First, it would be useful to examine whether the trends we identified up until 2015 continued especially during and after the COVID-19 pandemic. From an international perspective, comparative analyses might also aim to replicate our main results for other countries in order to examine whether theses trends are confined to Germany or reflect a broader development. Finally, since our paper is descriptive in nature, it does not provide a causal explanation of the shifting patterns of socio-economic segregation in Germany. Additional data and empirical strategies more focused on causal identification may help to make significant progress in this direction.

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A Appendix

A.1 Labor Market Reforms and Structural Breaks in the Data

Between 2003 and 2005, Germany introduced a comprehensive set of labor market reforms commonly referred to as 'Hartz-reforms'. These encompassed important regulatory changes regarding temporary work, marginal employment, active labor market policies, job placement services as well as unemployment insurance and benefits. This was accompanied by a profound restructuring of the German Federal Employment Agency. As a consequence, the very definition of what constitutes 'unemployment' changed in 2005 with significant effects on data collection and official statistics. This led to a structural break in the unemployment data, which, to the best of our knowledge, cannot be fully offset through sample selection and data adjustments in the raw data.

We address this data break in various ways throughout the paper in order to ensure that it does not impact our results. First, we chose the Theil Index as a segregation index that is composition invariant and as such neither reacts to the sudden increase in overall measured unemployment in 2005 nor to the ups and downs of unemployment throughout the business cycle. As a result, the transition from 2004 to 2005 in Figure 2 is smooth and part of a longer-term trend rather than resulting from a one-time level shift. This does not hold for the other segregation indices discussed in Appendix A.3.

Second, we add city-year specific fixed effects to our main regressions to control for overall or city-specific shifts in unemployment over time. This strategy is employed in Figures 3 and 4. As a result, only local differences in the size of the structural break may still influence our estimates. We verify that this potential caveat does not affect our main results by repeating these regressions excluding the years before 2005.

Third, we correct for trend breaks in a mechanical way whenever the above solutions do not work, which is the case for Figures 4 (right panel), 7, and C.11. Here, we use a Regression Discontinuity Design (RDD) to estimate the size of the trend break with the intent to thereafter factor it out. Figure C.13 shows the raw and uncorrected estimates for all three figures. With regard to the shift in average distance to the city center that underlie the right panel of Figure 7 it shows, for example, that average distances as expected change only slowly and continuously over the years since adjustments in location decisions take time. There is, however, a downward jump at the time of the structural break between 2004 and 2005. Addressing this issue, we extrapolate the 2000-2004 trend into 2005 and use the estimated gap to shift later years upwards in order to align the two periods.

A.2 Spatial Smoothing

While grid cells have the advantage that they provide a stable and consistent unit of measurement, one disadvantage is that they only provide a very inflexible definition of what a local neighborhood is. They might cut right through actual quarters and ignore close-by areas that still shape the living environment at a particular place (see, e.g., Flache and Hegselmann (2001)). Figure C.9 illustrates the problem. Each of the two boxes represent one city and each square refers to one grid cell. Red squares indicate neighborhoods with high local unemployment rates, green cells exhibit low levels of unemployment. Focusing on the cell marked with an "A", the cell-specific unemployment rate is equal (and low) in both cities. Still, for the city on the right, the population in "A" lives close to several high-unemployment areas, which may shape this residential area differently compared to the city on the left.

When it comes to measuring spatial unevenness with the Theil Index as defined in Equation (2), both distributions of grid cells would yield identical values for T_r. This is, however, misleading as the left region is arguably more uneven than the right one. The inability of 'aspatial' indicators to account for this difference has frequently been referred to as the 'checkerboard problem' (see, e.g., White (1983) and Morill (1991)).

Following Reardon and O'Sullivan (2004), we address this issue by means of spatial smoothing, i.e., for each cell we also consider the composition of neighboring cells in order to account for the local environment a cell is located in. Spatially smoothed variants of τ and π in Section 2.3 and all following sections are denoted by $\tilde{\tau}$ and $\tilde{\pi}$ with weights depending on the spatial proximity of two grid cells. We define the spatial proximity between two grid cells p and q in a region by means of a proximity function $\phi(p,q)$ with $\phi(p,q) = \phi(q,p)$ and $\phi(p,p) = \phi(q,q)$. Note that in the aspatial case $\phi(p,q) = 0$ and $\phi(p,p) = 1$. In the spatial case, we use an Epanechnikov kernel as weight function

$$\phi(p,q) = \begin{cases} \frac{3}{4}(1 - \frac{1}{5}z^2)\sqrt{5} & \text{if } \ |z| < \sqrt{5} \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

where $z = \frac{d(p,q)}{h}$. $d(p,q)$ is the Euclidian distance between grid cells p and q, and h is a bandwidth parameter that is set to 500 meters. As a result, $\tilde{\tau}_{prt}$ and $\tilde{\pi}_{prt}$ are spatially weighted averages over 12 grid cells forming a diamond shape around the center grid, where the outer grids are assigned about 1/5 of the weight of the center. This is illustrated in Figure C.9. Light green and light red cells are located closely to cell A. We include these 12 directly or indirectly adjacent cells (equal to an area of 3 km^2) into the calculation of the cell-specific unemployment rate and to generate the spatially augmented Theil Index $\tilde{T}_{rt}$, which is constructed as follows

$$\tilde{T}_{rt} = \frac{1}{N} \sum_p \tau_{prt} \frac{\tilde{\pi}_{prt}}{\pi_{rt}} \ln(\frac{\tilde{\pi}_{prt}}{\pi_{rt}}). \tag{11}$$

A.3 The Dissimilarity Index and the Information Theory Index as Alternative Indicators

For most part of the analysis, we use the Theil Index as our main indicator to measure and describe the extent and dynamics of spatial unevenness in the distribution of workers and the unemployed. However, the main results of our paper, like the rise of segregation over time as shown in Figure 2, do not depend on the choice of one particular indicator. To show this, we calculate the Dissimilarity Index $\tilde{D}_{rt}$ and the Information Theory Index $\tilde{H}_{rt}$ as two alternative measures for segregation that are widely used in the literature (see, e.g., Reardon and O'Sullivan (2004)). Using the notation introduced in Section 2.3

and $m = \{W, U\}$, the spatially smoothed variant of the Dissimilarity Index $\tilde{D}$ can be formulated as

$$\tilde{D}_{rt} = \sum_{m} \sum_{p} \frac{\tau_{prt}}{2N_{rt}I_{rt}} |\tilde{\pi}^{m}_{prt} - \pi^{m}_{rt}|, \tag{12}$$

where I_{rt} is the interaction index

$$I_{rt} = \sum_{m} (\pi^{m}_{rt})(1 - \pi^{m}_{rt}). \tag{13}$$

The spatial variant of the Information Theory Index is calculated as

$$\tilde{H}_{rt} = 1 - \frac{1}{N_{rt}E_{rt}} \sum_{p} \tau_{prt} \tilde{E}_{prt}, \tag{14}$$

with spatially weighted local entropy $\tilde{E}_{prt}$ and overall regional entropy E_{rt} defined as

$$\tilde{E}_{prt} = -\textstyle\sum_{m} (\tilde{\pi}^{m}_{prt}) \log_2(\tilde{\pi}^{m}_{prt}) \tag{15}$$

$$E_{rt} = -\textstyle\sum_{m} (\pi^{m}_{rt}) \log_2(\pi^{m}_{rt}). \tag{16}$$

Figure C.4 illustrates the dynamics of segregation when using the Dissimilarity Index in the left panel and the Information Theory Index in the right panel. Both indices show a pattern that is qualitatively similar to the one in Figure 2. At the same time they do, however, exhibit a trend break between 2004 and 2005 as a result of the structural change in unemployment measurement discussed in Appendix A.1. To illustrate the relevance of the break in the data more clearly, Figure C.14 contrasts the average population-weighted Information Theory Index (left panel) and Theil Index (right panel) for the 80 regions. While the structural break is clearly visible for the Information Theory Index, the time series evolves smoothly for the Theil Index. This result once again corroborates the importance of choosing a segregation index that is compositionally invariant in a dynamic macroeconomic environment.

In addition the Theil Index, the Dissimilarity Index and the Information Theory Index, we have computed a range of alternative segregation indices suggested by Reardon and O'Sullivan (2004) in both their both spatial and aspatial variants. These encompass the Isolation Index, Exposure Index, and Relative Diversity Index. We do not discuss these indices further in this paper; results are available upon request.

A.4 Recentered Influence Functions for the Segregation Measures

In several parts of the paper, we use Recentered Influence Functions (RIFs) to analyze the contributions of individual grid cells to the level of segregation and localization in a city (see, e.g., Sections 4.2 and 6.2). Drawing on the exposition in Cowell and Flachaire (2007), we explain the derivation of these RIFs in greater detail here. Assume a random variable y with probability distribution F and an inequality measure $I(F)$. The idea behind an Influence Function (IF) is that there might be a small perturbation to F at point z, with H as the cumulative density function of that perturbation

$$H(y) = \mathbf{1}(y \geq z). \tag{17}$$

This leads to the mixed distribution

$$G_\epsilon = (1-\epsilon)F + \epsilon H, \tag{18}$$

where $0 < \epsilon < 1$. The influence of an infinitesimal model deviation on I is given by $\partial I(G_\epsilon)/\partial\epsilon|_{\epsilon=0}$. The RIF is then derived by adding $I(F)$ to the IF. For the Theil Index (Section 3.1), we have

$$T = \int \frac{y}{\mu} \log\left(\frac{y}{\mu}\right) \mathrm{d}F(y) = \frac{v}{\mu} - \log\mu, \tag{19}$$

with $v = \int y \log y \ \mathrm{d}F(y)$ and $\mu = \int y \ \mathrm{d}F(y)$. Introducing the mixed distribution G_ϵ to the index, we get

$$v_{G_\epsilon} = (1-\epsilon)\int y\log y \ \mathrm{d}F(y) + \epsilon z \log z \quad \text{and} \quad \mu_{G_\epsilon} = (1-\epsilon)\int y \ \mathrm{d}F(y) + \epsilon z. \tag{20}$$

This leads to

$$\begin{aligned} IF(z;T,F) &= -\frac{z-\mu}{\mu^2}\int y\log y \ \mathrm{d}F(y) + \frac{1}{\mu}\left(-\int y\log y \ \mathrm{d}F(y) + z\log z\right) - \frac{z-\mu}{\mu} \\ &= \frac{z\log z - v}{\mu} - \frac{v+\mu}{\mu^2}(z-\mu). \end{aligned} \tag{21}$$

For the Localization Index (Section 6.1), we have

$$L = \int_p \frac{y_p}{\mu}\log\left(\frac{y_p}{\tilde{y}_p}\right) \mathrm{d}F(y_p), \tag{22}$$

with $\tilde{y}_p = \int_q \omega_{qp} y_q \ \mathrm{d}F(y_q)$. Here, subscript p runs over the main observations of y and subscript q over nearby observations, with distance-related weights defined by ω. Introducing the mixed distribution G_ϵ to the index, we get

$$L(G_\epsilon) = \mu_{G_\epsilon}^{-1}\left[v_{G_\epsilon} - \int_p y\log((1-\omega_{qp}\epsilon)\tilde{y}_p + \omega_{qp}\epsilon z)\mathrm{d}F(y_p)\right]. \tag{23}$$

For the Influence Function, this leads to

$$IF(z_p;L,F) = \frac{z_p\log z_p - v_p}{\mu} - \frac{L}{\mu}(z_p-\mu) - \frac{1}{\mu}\left[\int_q \frac{y_q\omega_{qp}}{\tilde{y}_q}(z_p - \tilde{y}_q)\mathrm{d}F(y_q)\right]. \tag{24}$$

The last part of Equation (24) captures the fact that adding a perturbation z at location p not only affects the Localization Index directly but also indirectly by spilling over to neighboring areas and altering the locally weighted measure $\tilde{y}$ there.

B Additional Tables

Table B.1: Cities and Populations

City	*Population*	*City*	*Population*
Berlin*	3,677,472	Hagen	188,713
Hamburg*	1,853,935	Potsdam*	183,154
Munich*	1,487,798	Saarbrücken	179,634
Cologne*	1,073,096	Hamm	179,238
Frankfurt(Main)*	759,224	Ludwigshafen*	172,145
Stuttgart*	626,275	Mülheim a.d. Ruhr	170,739
Düsseldorf*	619,477	Oldenburg(Oldb)*	170,389
Leipzig*	601,866	Osnabrück*	165,034
Dortmund	586,852	Leverkusen*	163,851
Essen	579,432	Darmstadt*	159,631
Bremen*	563,290	Heidelberg*	159,245
Dresden*	555,351	Solingen	158,957
Hanover*	535,932	Herne	156,621
Nuremberg*	510,632	Regensburg*	153,542
Duisburg*	495,152	Neuss*	152,731
Bochum	363,441	Paderborn*	152,531
Wuppertal	354,572	Ingolstadt*	138,016
Bielefeld*	334,002	Offenbach am Main*	131,295
Bonn*	331,885	Würzburg*	129,122
Münster*	317,713	Fürth*	126,949
Mannheim*	311,831	Ulm*	126,933
Karlsruhe*	306,502	Heilbronn*	125,613
Augsburg*	296,478	Pforzheim*	125,529
Wiesbaden*	278,950	Wolfsburg*	123,949
Mönchengladbach*	261,001	Bottrop	117,311
Gelsenkirchen	260,126	Göttingen	116,557
Aachen*	249,070	Reutlingen*	116,456
Braunschweig*	248,832	Koblenz*	113,638
Kiel*	246,243	Erlangen*	113,292
Chemnitz	243,105	Bremerhaven	113,173
Halle(Saale)*	238,061	Remscheid	111,770
Magdeburg	236,188	Bergisch Gladbach*	111,645
Freiburg im Breisgau*	231,848	Recklinghausen	110,714
Krefeld*	227,050	Trier*	110,570
Mainz*	217,556	Jena	110,502
Lübeck*	216,277	Moers*	103,725
Erfurt	213,227	Salzgitter*	103,694
Oberhausen*	208,752	Siegen*	101,516
Rostock	208,400	Gütersloh*	101,158
Kassel*	200,406	Hildesheim	100,319

Notes: The table lists all cities in Germany with a population of more than 100,000 inhabitants as of December 31st, 2021. Cities marked by an asterisk (*) exhibit a growing number of persons in the labor force between 2000 and 2015 according to our measurement (see Section 2.3). **Sources:** Statistisches Bundesamt (2022); calculations of changes in the labor force are based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Table B.2: Number of Workers and Unemployed

Year	*Workers*	*Unemployed*	*Benefit Recipients*
2000	20,396,115	2,871,275	
2001	20,639,998	2,775,820	
2002	20,365,157	2,973,501	
2003	19,946,042	3,337,305	
2004	19,800,981	3,441,289	
2005	19,387,195	4,159,429	
2006	19,545,407	3,798,111	4,370,840
2007	19,954,944	3,327,930	4,398,046
2008	20,317,882	2,930,977	4,257,645
2009	20,189,233	3,046,832	4,188,093
2010	20,355,177	2,878,729	4,286,327
2011	20,771,862	2,670,931	4,094,057
2012	21,082,423	2,627,740	3,991,017
2013	21,337,907	2,674,149	4,026,272
2014	21,629,796	2,611,623	4,062,823
2015	21,918,181	2,542,397	4,037,442

Notes: The table provides the number of workers and unemployed (as defined in Section 2.3) contained in the data set per year. The last column shows the number of benefits recipients (see Section 3.2).
Sources: own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Table B.3: List of Theil Indices for all Cities

City	*2000*	*2015*	Δ	*City*	*2000*	*2015*	Δ
Aachen	0.092	0.192	0.100	Koblenz	0.134	0.257	0.123
Augsburg	0.126	0.236	0.110	Krefeld	0.114	0.240	0.126
Bergisch Gladbach	0.108	0.199	0.092	Köln	0.116	0.209	0.092
Berlin	0.075	0.176	0.101	Leipzig	0.053	0.203	0.150
Bielefeld	0.163	0.241	0.077	Leverkusen	0.108	0.195	0.087
Bochum	0.082	0.184	0.102	Ludwigshafen a.R.	0.125	0.237	0.112
Bonn	0.110	0.231	0.121	Lübeck	0.135	0.276	0.141
Bottrop	0.079	0.179	0.100	Magdeburg	0.063	0.231	0.169
Braunschweig	0.088	0.295	0.207	Mainz	0.116	0.213	0.097
Bremen	0.130	0.294	0.164	Mannheim	0.116	0.221	0.105
Bremerhaven	0.145	0.341	0.196	Moers	0.110	0.237	0.127
Chemnitz	0.051	0.266	0.215	Mönchengladbach	0.109	0.225	0.116
Cottbus	0.067	0.327	0.260	Mülheim a.d.R.	0.096	0.205	0.109
Darmstadt	0.099	0.180	0.080	München	0.078	0.156	0.078
Dortmund	0.087	0.193	0.106	Münster	0.140	0.235	0.095
Dresden	0.064	0.254	0.190	Neuss	0.102	0.188	0.086
Duisburg	0.105	0.225	0.120	Nürnberg	0.125	0.250	0.125
Düsseldorf	0.107	0.205	0.098	Oberhausen	0.083	0.191	0.107
Erfurt	0.068	0.242	0.174	Offenbach a.M.	0.103	0.178	0.075
Erlangen	0.123	0.270	0.147	Oldenburg	0.129	0.282	0.153
Essen	0.094	0.196	0.103	Osnabrück	0.179	0.325	0.146
Frankfurt a.M.	0.117	0.205	0.088	Paderborn	0.150	0.216	0.067
Freiburg i.B.	0.138	0.228	0.089	Pforzheim	0.131	0.336	0.205
Fürth	0.109	0.222	0.114	Potsdam	0.093	0.240	0.147
Gelsenkirchen	0.070	0.168	0.098	Recklinghausen	0.063	0.137	0.074
Göttingen	0.110	0.243	0.133	Regensburg	0.158	0.299	0.141
Hagen	0.102	0.217	0.115	Remscheid	0.089	0.200	0.111
Halle (Saale)	0.054	0.273	0.219	Reutlingen	0.120	0.222	0.102
Hamburg	0.116	0.205	0.088	Rostock	0.068	0.279	0.211
Hamm	0.121	0.266	0.145	Saarbrücken	0.133	0.280	0.147
Hannover	0.119	0.214	0.095	Salzgitter	0.098	0.258	0.160
Heidelberg	0.102	0.172	0.070	Siegen	0.137	0.301	0.164
Heilbronn	0.143	0.247	0.104	Solingen	0.090	0.190	0.100
Herne	0.062	0.140	0.079	Stuttgart	0.104	0.183	0.079
Hildesheim	0.122	0.328	0.206	Trier	0.172	0.273	0.101
Ingolstadt	0.181	0.432	0.251	Ulm	0.127	0.256	0.129
Jena	0.092	0.230	0.138	Wiesbaden	0.121	0.228	0.107
Karlsruhe	0.107	0.211	0.104	Wolfsburg	0.101	0.384	0.283
Kassel	0.134	0.309	0.175	Wuppertal	0.096	0.205	0.109
Kiel	0.142	0.370	0.228	Würzburg	0.151	0.279	0.129

Notes: The table lists the spatially smoothed Theil Indices $\tilde{T}_{rt}$ for all 80 regions used in the analysis (see Section 3). It shows that the spatial unevenness in the distribution of unemployment rates has risen across the board. The calculation uses both the core and hinterland of a city. Variants that only use the core or other segregation measures (see Appendix A.3) are available upon request. **Sources:** own calculation based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

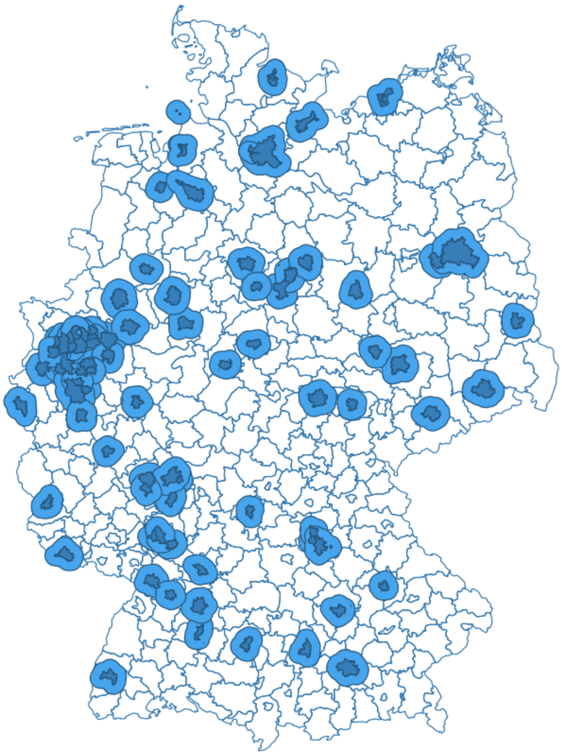
Table B.4: List of Localization Indices for all Cities

City	*2000*	*2015*	Δ	*City*	*2000*	*2015*	Δ
Aachen	0.029	0.053	0.024	Koblenz	0.059	0.097	0.039
Augsburg	0.059	0.067	0.008	Krefeld	0.034	0.043	0.009
Bergisch Gladbach	0.037	0.057	0.020	Köln	0.037	0.057	0.020
Berlin	0.017	0.038	0.021	Leipzig	0.018	0.057	0.040
Bielefeld	0.072	0.089	0.017	Leverkusen	0.031	0.051	0.020
Bochum	0.026	0.039	0.013	Ludwigshafen a.R.	0.041	0.065	0.025
Bonn	0.056	0.083	0.026	Lübeck	0.049	0.076	0.027
Bottrop	0.026	0.039	0.013	Magdeburg	0.019	0.068	0.049
Braunschweig	0.038	0.087	0.050	Mainz	0.047	0.072	0.024
Bremen	0.041	0.064	0.023	Mannheim	0.042	0.068	0.026
Bremerhaven	0.040	0.057	0.018	Moers	0.031	0.041	0.010
Chemnitz	0.024	0.098	0.074	Mönchengladbach	0.040	0.054	0.014
Cottbus	0.028	0.081	0.054	Mülheim a.d.R.	0.030	0.041	0.011
Darmstadt	0.051	0.074	0.024	München	0.042	0.065	0.023
Dortmund	0.028	0.046	0.018	Münster	0.066	0.092	0.026
Dresden	0.029	0.080	0.051	Neuss	0.036	0.053	0.017
Duisburg	0.032	0.044	0.012	Nürnberg	0.035	0.061	0.027
Düsseldorf	0.034	0.051	0.017	Oberhausen	0.026	0.038	0.012
Erfurt	0.024	0.069	0.044	Offenbach a.M.	0.041	0.061	0.020
Erlangen	0.036	0.073	0.037	Oldenburg)	0.065	0.112	0.047
Essen	0.029	0.042	0.013	Osnabrück	0.079	0.110	0.031
Frankfurt a.M.	0.046	0.066	0.021	Paderborn	0.062	0.081	0.019
Freiburg i.B.	0.055	0.079	0.025	Pforzheim	0.060	0.078	0.019
Fürth	0.030	0.055	0.025	Potsdam	0.026	0.052	0.026
Gelsenkirchen	0.026	0.042	0.016	Recklinghausen	0.026	0.038	0.013
Göttingen	0.036	0.079	0.043	Regensburg	0.072	0.129	0.057
Hagen	0.036	0.060	0.025	Remscheid	0.031	0.042	0.011
Halle (Saale)	0.017	0.066	0.049	Reutlingen	0.063	0.103	0.040
Hamburg	0.046	0.061	0.016	Rostock	0.021	0.053	0.032
Hamm	0.048	0.075	0.027	Saarbrücken	0.040	0.072	0.032
Hannover	0.042	0.070	0.028	Salzgitter	0.034	0.083	0.049
Heidelberg	0.046	0.077	0.031	Siegen	0.073	0.125	0.052
Heilbronn	0.057	0.086	0.029	Solingen	0.030	0.046	0.016
Herne	0.026	0.039	0.014	Stuttgart	0.045	0.075	0.030
Hildesheim	0.053	0.074	0.022	Trier	0.071	0.120	0.049
Ingolstadt	0.083	0.161	0.078	Ulm	0.062	0.114	0.052
Jena	0.024	0.058	0.035	Wiesbaden	0.049	0.077	0.028
Karlsruhe	0.048	0.082	0.034	Wolfsburg	0.046	0.129	0.082
Kassel	0.037	0.080	0.042	Wuppertal	0.037	0.051	0.014
Kiel	0.035	0.051	0.016	Würzburg	0.069	0.109	0.041

Notes: The table lists the Localization Indices L_{rt} for all 80 regions used in the analysis (see Section 6.1). It shows that the distribution of unemployment rates has become more localized in every region. The calculation uses both the core and hinterland of a city. Variants that only use the core cities are available upon request. **Sources:** own calculation based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

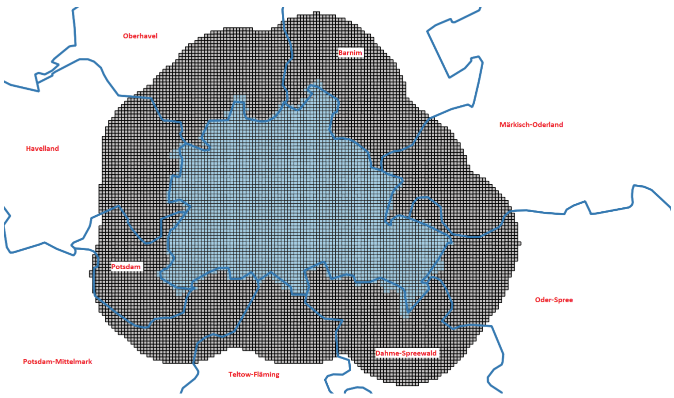
C Additional Figures

Figure C.1: Cities and Hinterlands



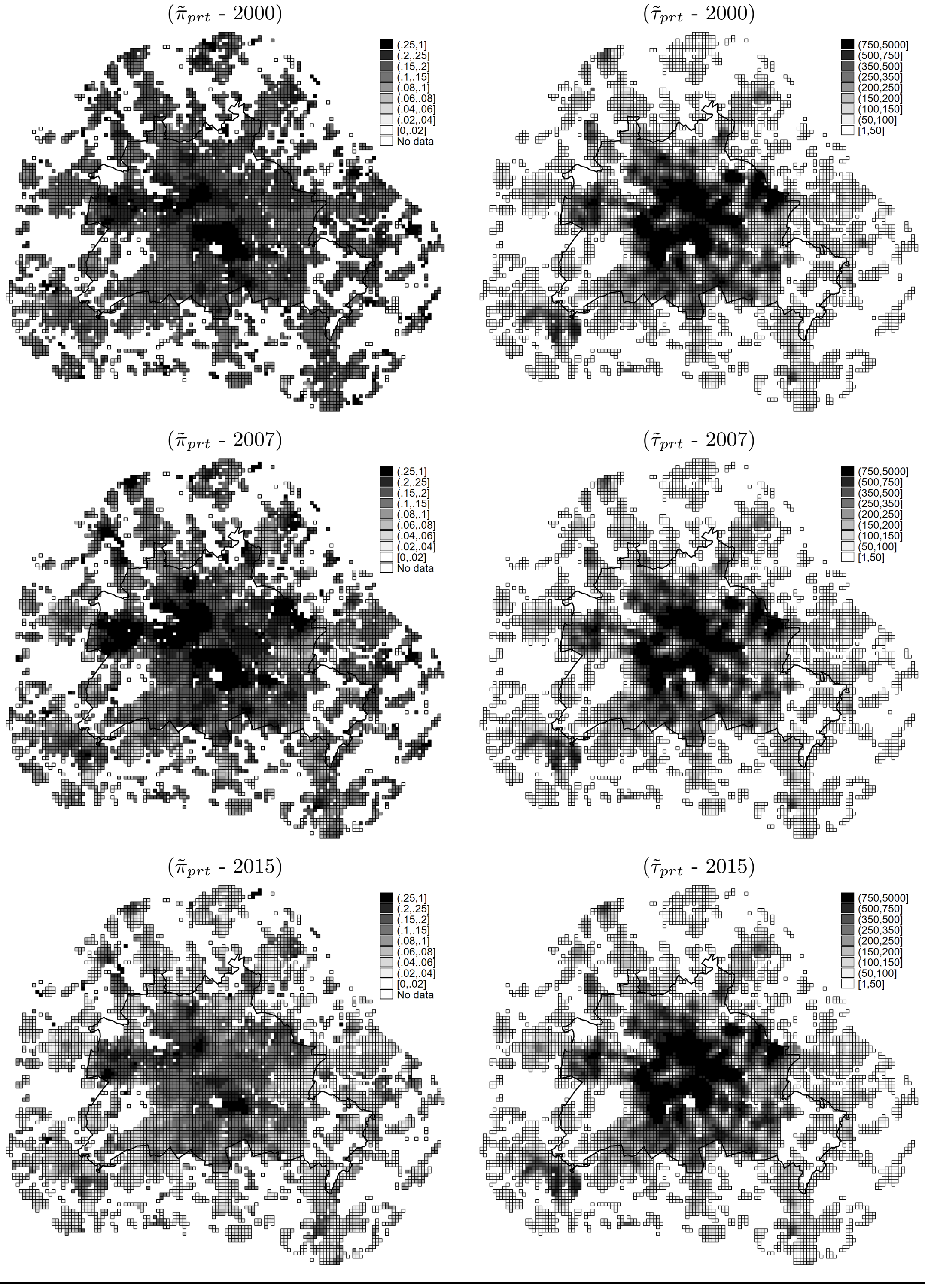
Notes: The figure shows the 80 largest cities in Germany (dark blue) and their corresponding hinterland (light blue). The combination of a core city and its hinterland form a 'region'. Areas outside this selection are not part of our analysis. **Source:** own representation. **Layers:** © GeoBasis-DE / BKG 2017.

Figure C.2: Cities and Grid Cells - The Case of Berlin



Notes: The figure shows the grid cells (500 x 500 meters) for the city of Berlin (blue color; 2,989 cells) and the surrounding hinterland (gray color; 3,266 cells). **Source:** own representation. **Layers:** © GeoBasis-DE / BKG 2017.

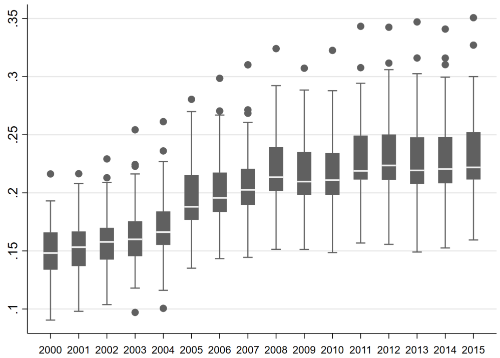
Figure C.3: Distribution of Unemployment and Labor Force in Berlin



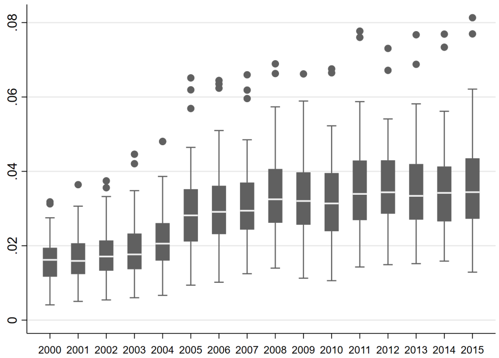
Notes: The figure shows the grid-cell specific unemployment rate $\tilde{\pi}_{prt}$ (left column) and the grid-cell specific labor force density $\tilde{\tau}_{prt}$ (right column) for different years (spatially weighted variants). Darker shades of gray indicate a higher local unemployment rate (labor force density). Grid cells with less than five persons per cell are excluded for reasons of data privacy. **Sources:** own representation based on the IEB (V13.01.00-181010) and IEB GEO (V01.00.00-201504). **Layers:** © GeoBasis-DE / BKG 2017.

Figure C.4: Alternative Measures of Segregation

Dissimilarity Index $\tilde{D}_{rt}$



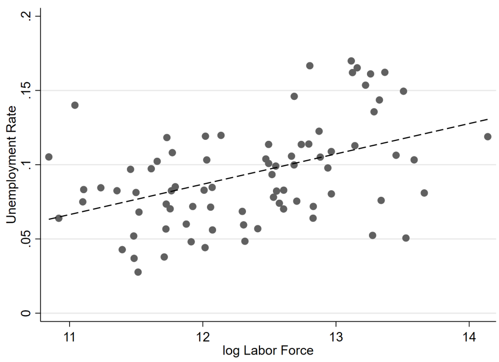
Information Theory Index $\tilde{H}_{rt}$



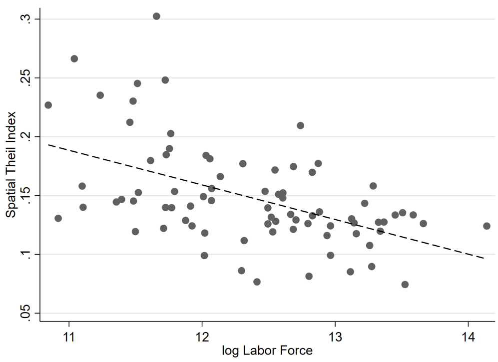
Notes: The left panel shows the distribution of the region-specific spatially smoothed Dissimilarity Index for the 80 largest cities and their hinterland in Germany by year; the right panel provides the same information based on the Information Theory Index. Their respective computations is detailed in Appendix A.3. Both indices follow the same pattern as the Theil Index (see Figure 2). **Sources:** own representation based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.5: City Size, Unemployment, and Spatial Unevenness

City Size & Unemployment

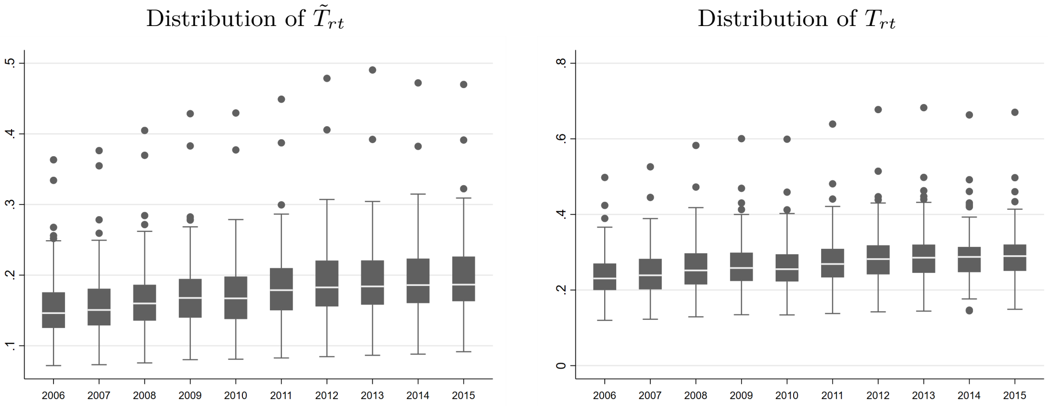


City Size & Spatial Unevenness



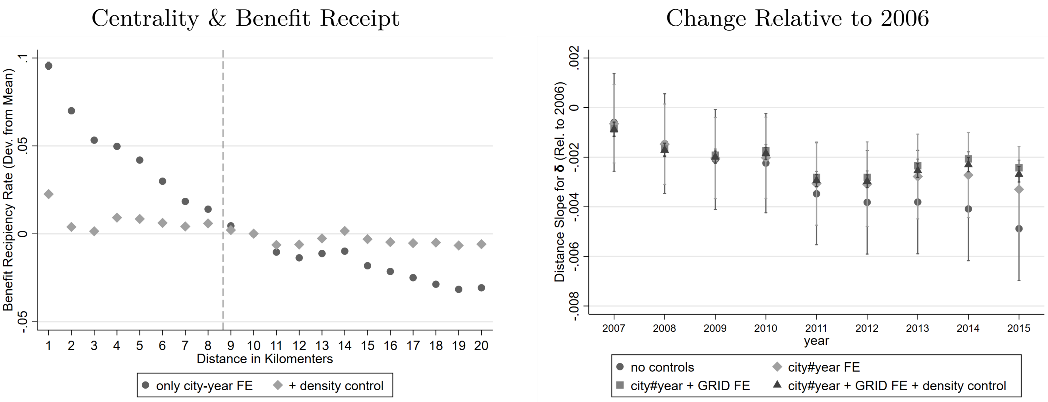
Notes: The left panel relates region-specific unemployment rates (including the hinterland) for the 80 largest cities in Germany in 2015 to the number of persons in the labor force (in logs) within the same region in the same year. The right panel plots the region-specific value of the spatial Theil Index in 2015 against log labor force (estimated using city size weights). The figure shows that larger regions exhibit on average higher unemployment rates with unemployment at the same time being spatially more evenly distributed. **Sources:** own representation based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.6: Social Benefit Recipients - Spatial Unevenness over Time



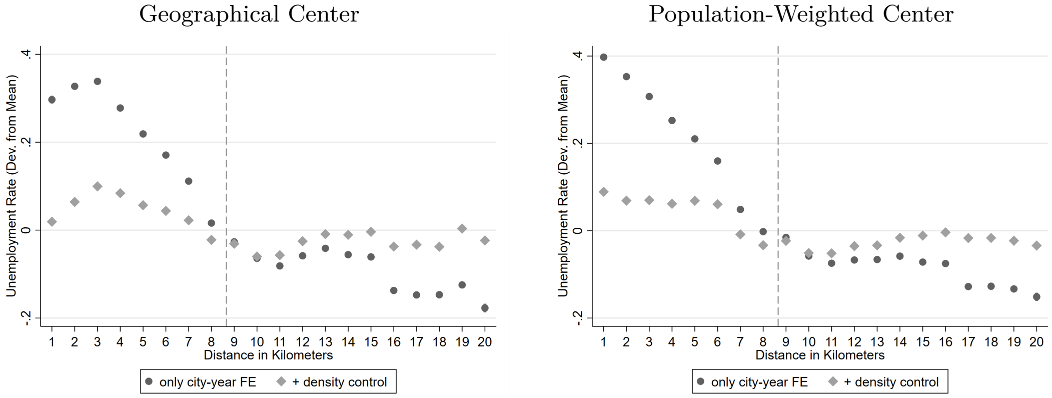
Notes: The left panel shows boxplots of the spatially smoothed Theil Indices $\tilde{T}_{rt}$ of the benefit recipient rate for the 80 largest cities in Germany (including their hinterland) between 2000 and 2015. In the right panel, $\tilde{T}_{rt}$ is replaced by the 'aspatial' T_{rt}. The figure demonstrates that spatial unevenness is also rising when using a different socio-economic measure than our preferred one (the unemployment rate). **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.7: Centrality and Social Benefit Recipients



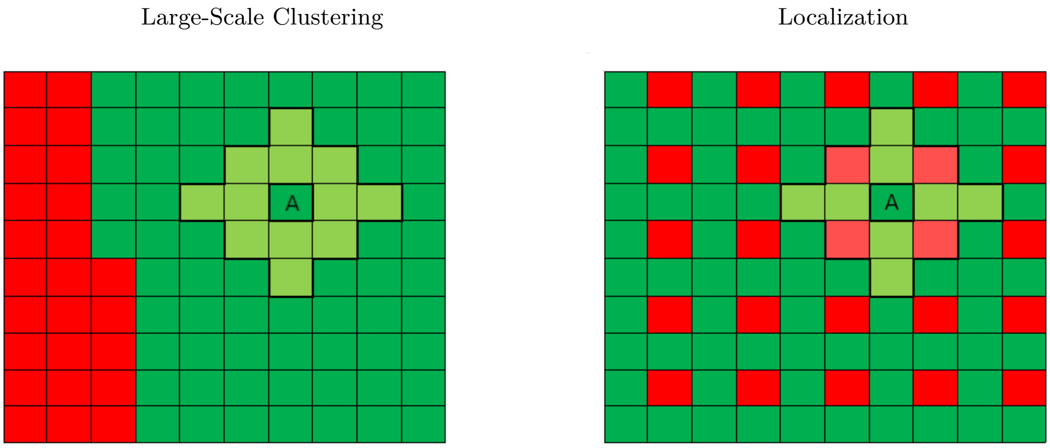
Notes: The left panel shows the spatially smoothed local benefit recipient rate (as deviations from the city-specific mean) by distance to the center, pooled for the 80 regions and the years 2006 to 2015. The model controls for city-year fixed effects. "+ density control" indicates that the model also controls for labor force density. The right panel shows the gradient between the local benefit recipient rate and distance to the center for 2007 to 2015 (relative to the gradient in 2006). It contains model variants (i) without further controls, (ii) including city-year fixed effects, (iii) including grid-cell specific and city-year fixed effects and (iv) both sets of fixed effects plus log labor force density as a control. The dashed line represents the average distance from the city center to the border between the city and the hinterland. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.8: Centrality and Unemployment - Alternative City Centers



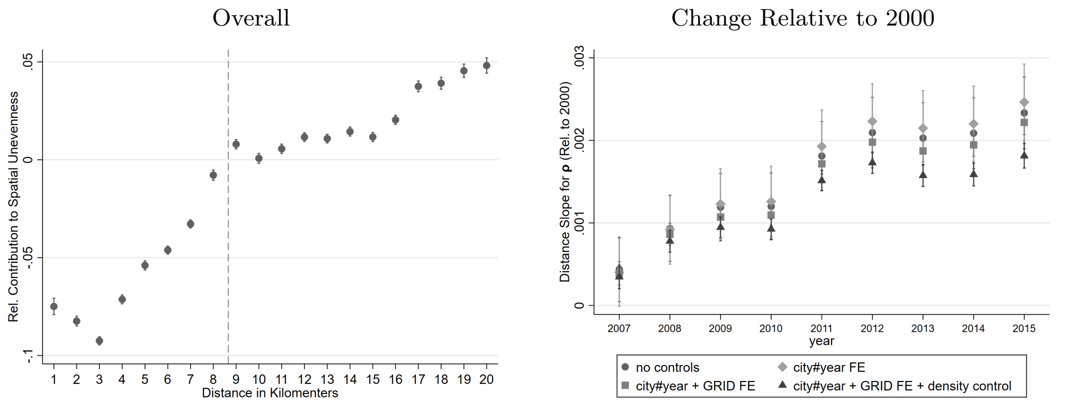
Notes: The figure is conceptually identical with the right panel of Figure 3 in the main text body but draws on the geographic center (left) and the population-weighted center (right) as alternative midpoints of a city. It shows the spatially smoothed local unemployment rate (as deviations from the city-specific mean) by distance to the center. The dashed line represents the average distance from the city center to the border between the city and the hinterland. All models control for city-year fixed effects. "+ density control" indicates that the model also controls for labor force density. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.9: The Checkerboard Problem and Spatial Smoothing



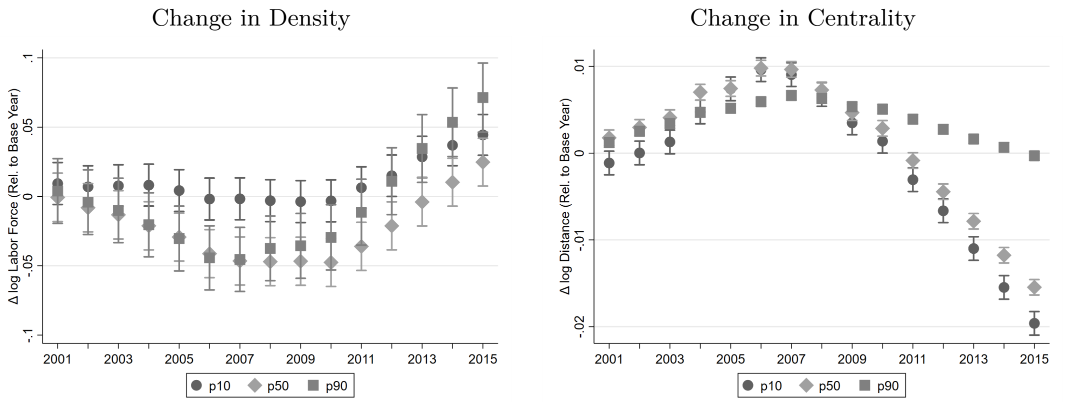
Notes: The figure illustrates our method of spatial smoothing as explained in Appendix A.2. The left and the right box each represent one city. Within each of them, one square refers to a grid cell with high (red squares) or low (green squares) unemployment rates. Light green and light red cells are those cells that are directly or indirectly adjacent to cell A. To derive the smoothed indices, cell A receives the highest weight, adjacent cells a lower weight, and further away cells no weight. **Source:** own representation.

Figure C.10: Spatial Unevenness and Centrality over Time - Benefit Recipients



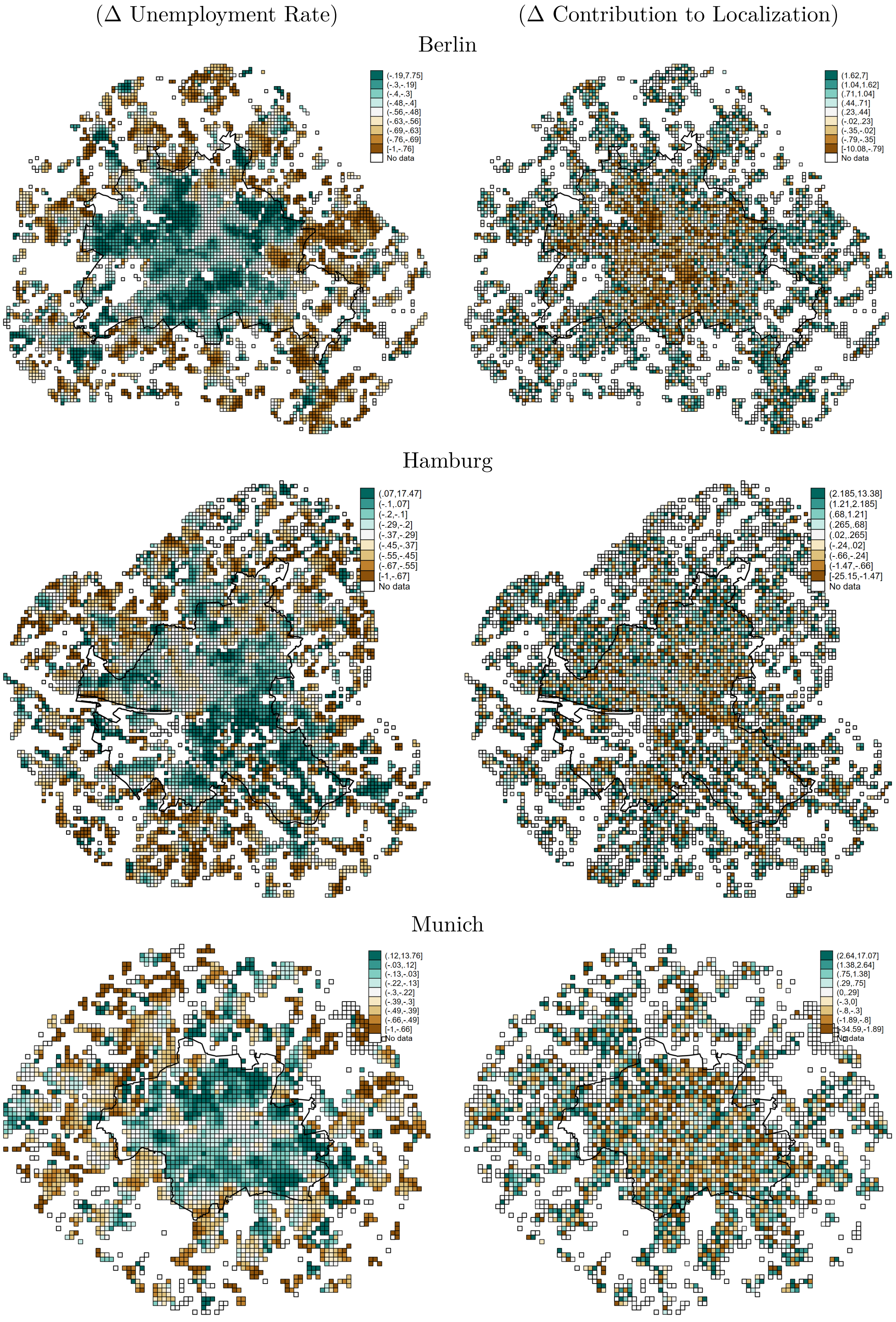
Notes: The left panel shows the relative contribution of grid cells to the region-wide spatial unevenness in the distribution of benefit recipients (estimates by distance bin to the city center, pooled for all years and 80 regions and controlling for city-year fixed effects). It shows that peripheral areas contribute relatively more to within-city segregation than the center. The right panel shows the gradient between this relative contribution and distance to the center for 2015 relative to the gradient in 2006. It contains model variants (i) without further controls, (ii) including city-year fixed effects, (iii) including city-year and grid-cell specific fixed effects and (iv) additionally controlling for local labor force density. It shows that the role of the periphery in driving overall segregation has increased over time. The dashed line represents the average distance from the city center to the border between the city and the hinterland. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.11: Suburbanization and Reurbanization - Quantiles of the Distribution



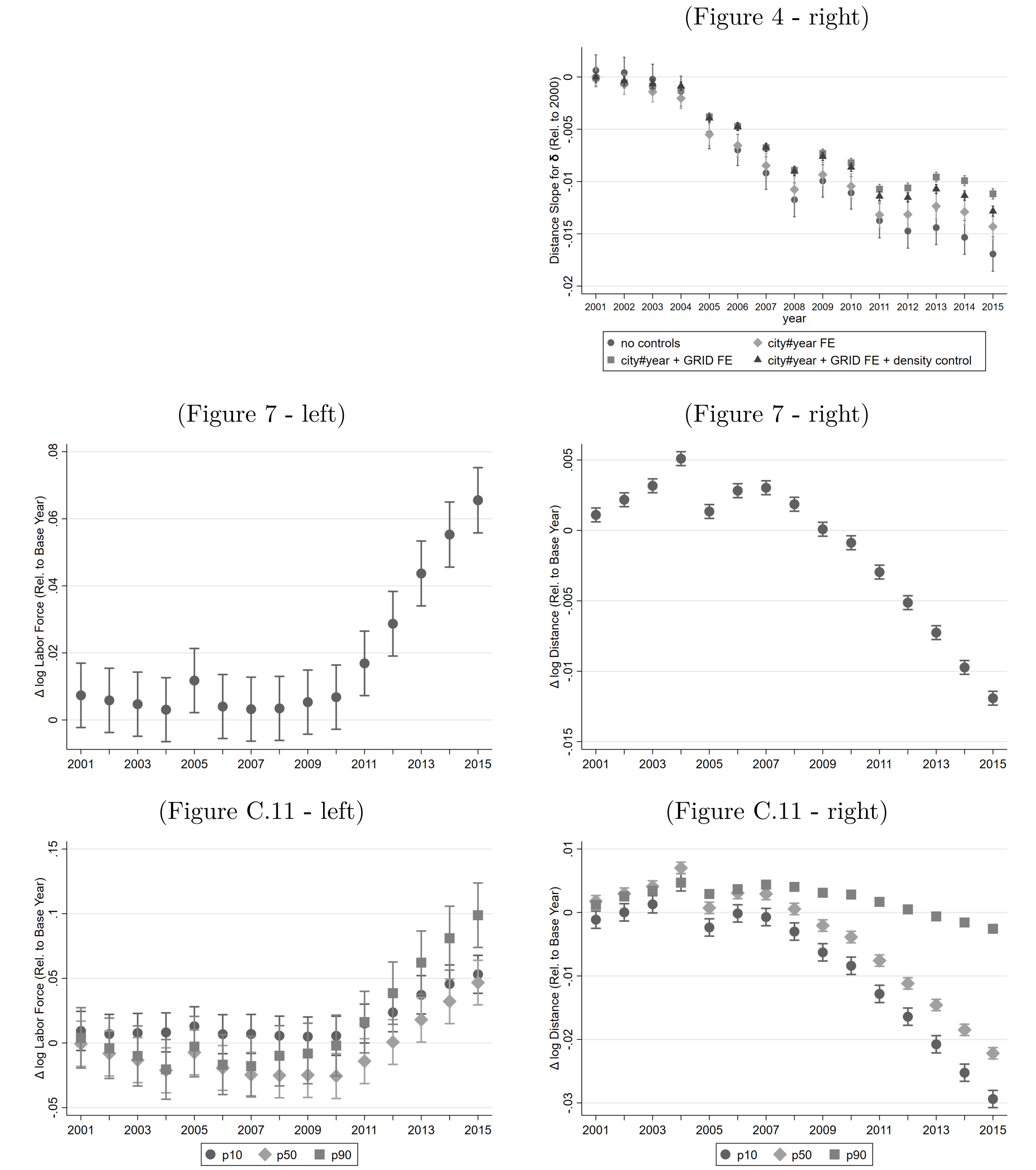
Notes: The graph plots estimates for three percentiles of the distribution of density and centrality (p10, p50 and p90). The left panel shows the percentage change in labor force density per grid cell relative to 2000. The right panel shows the percentage change in the distance of the labor force from the city center. Both graphs pool all 80 regions and control for city-specific fixed effects to identify shifts from within-city variation alone. It shows that the process of reurbanization was mainly directed at the city centers. For details on the correction of a structural break in 2005, see Appendix A.1. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.12: Change in Unemployment and Contribution to Localization



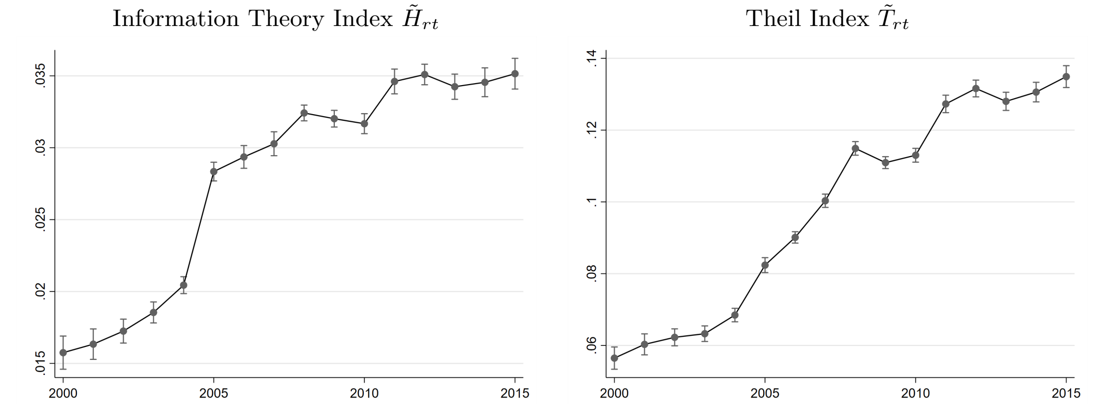
Notes: The figure shows the grid-cell specific percentage change in unemployment rates (left column) and the change in contribution to city-level localization (right column) for the three largest German cities (Berlin, Hamburg, Munich) as 2000-2015 long differences. Brown shades represent above-average reductions in unemployment rates (or falling contributions to localization), green shades below-average reductions in unemployment rates (or rising contributions to localization). Grid cells with less than five persons per cell had to be excluded. For details on calculating cell-specific Influence Functions for localization, see Appendix A.4. The figure demonstrates that localization was more strongly driven by the hinterlands, where unemployment also fell the most. **Sources:** own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504). **Layers:** © GeoBasis-DE / BKG 2017.

Figure C.13: Figures Excluding Trend-Break Adjustment



Notes: The figure shows the raw, uncorrected variants of all figures in this paper that rely on the trend-break adjustment by means of the Regression Discontinuity Design (RDD) outlined in Appendix A.1.
Sources: own calculations based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).

Figure C.14: Alternative Measures of Segregation - Structural Breaks



Notes: The left panel shows the average population-weighted and spatially-smoothed Information Theory Indices for the 80 largest cities and their hinterland in Germany for the years 2000 to 2015 including 95% confidence bands; the right panel shows the same for the Theil Index. The figure shows that the Information Theory Index is not composition invariant and therefore exhibits a significant trend break in 2005. See Appendix A.2 for a discussion. **Sources:** own representation based on the IEB (V13.01.00-181010) and the IEB GEO (V01.00.00-201504).