IWH
Halle Institute for Economic Research
Member of the Leibniz Association

Discussion Papers
No. 4
April 2026

Growth Clubs and Regional Economic Convergence in Germany

Oliver Holtemöller, Christoph Schult, Anna Solms

https://doi.org/10.18717/dpakdx-vs40

Authors

Oliver Holtemöller
Halle Institute for Economic Research (IWH) –
Member of the Leibniz Association,
Department of Macroeconomics, and
Martin Luther University Halle-Wittenberg
E-mail: oliver.holtemoeller@iwh-halle.de
Tel +49 345 7753 800

Christoph Schult
Halle Institute for Economic Research (IWH) –
Member of the Leibniz Association,
Department of Macroeconomics
E-mail: christoph.schult@iwh-halle.de
Tel +49 345 7753 806

Anna Solms
Halle Institute for Economic Research (IWH) –
Member of the Leibniz Association,
Department of Macroeconomics
E-mail: anna.solms@iwh-halle.de
Tel +49 345 7753 804

The responsibility for discussion papers lies solely with the individual authors. The views expressed herein do not necessarily represent those of IWH. The papers represent preliminary work and are circulated to encourage discussion with the authors. Citation of the discussion papers should account for their provisional character; a revised version may be available directly from the authors.

Comments and suggestions on the methods and results presented are welcome.

IWH Discussion Papers are indexed in RePEc-EconPapers and in ECONIS.

Editor

Halle Institute for Economic Research (IWH) –
Member of the Leibniz Association

Address: Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany
Postal Address: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Growth Clubs and Regional Economic Convergence in Germany

Abstract

Many countries and regions remain below the level of economic activity of the world's most advanced economies. Some countries form growth clubs, some are stuck in the middle-income trap, and some stay on a very low level of economic activity. Although this situation is well documented on the country level, there is less evidence at the sub-national level within countries. We estimate county-level capital stocks and price indices and provide a comprehensive county-level data set for Germany. We find no evidence of convergence across all counties even if we condition on important drivers of long-term growth such as physical and human capital accumulation. Instead, we identify five convergence clubs, using endogenous clustering. We analyze differences in growth paths and describe the identified clusters based on variations in contributions of capital, labor, and total factor productivity to economic growth. Additionally, we examine the role of migration for regional development and find that net migration has in particular contributed to growth in richer regions.

Keywords: convergence clubs, growth accounting, regional economic growth

JEL classification: C23, O47, R11

1 Introduction

Economic convergence across and within countries is an important topic in economic policy debates. Although gross domestic product per capita is a reasonable proxy for welfare, it neglects factors such as consumption possibilities, leisure time, life expectancy, and inequality (Jones and Klenow, 2016). We describe regional inequality in economic activity and analyze the determinants of heterogeneous levels and growth rates of output within countries.

The neoclassical growth model (Solow, 1956) predicts that poor regions grow faster than rich ones. In particular, there exist three different notions of convergence. The *absolute convergence* hypothesis suggests that regions converge to one another, regardless of initial conditions (Baumol, 1986). As the long-term equilibrium of an economy is based on its structural characteristics, convergence would involve the harmonization of structural features between regions. However, this hypothesis has been opposed in several studies, for instance in Lucas (1988), or Barro (1991). The *conditional convergence* theory suggests that regions with similar structural conditions, for example, in their technologies, demographic characteristics, saving rates, and institutions, converge to the same level of economic activity, regardless of their initial characteristics (Mankiw et al., 1992; Barro and Sala-i-Martin, 1995).

The *club convergence* hypothesis indicates that regions with similar structural conditions converge only if their initial conditions are also matched (Durlauf and Johnson, 1995; Quah, 1994).

While many early studies on economic convergence focus on the national perspective, more recent literature has studied the role of within-country heterogeneity. For example, Young et al. (2008) find conditional convergence of US states, Zhang et al. (2019) analyze Chinese prefecture-level regions to find regional club convergence, while Bartkowska and Riedl (2012) and von Lyncker and Thoennessen (2017) find evidence for club convergence across the NUTS-2 regions (level 2 of the Nomenclature of Territorial Units for Statistics) in the European Union (EU). For the US, Arif (2022) study income per capita convergence of metropolitan areas, which are similar to EU NUTS-2 regions. The only existing study that, to our knowledge, investigates club convergence at a more granular level is Chatterji and Dewhurst (1996), who examine English and Welsh counties for the period 1977–1991, using income gap metrics to identify convergence patterns. Gennaioli et al. (2013) have documented considerable income inequality among regions within countries: they find that the richest region in a country exhibits, on average, four times more economic activity than the poorest region. Although a large fraction of within-country variation occurs on the regional level, empirical research on convergence in the EU has largely focused on the NUTS-2 regions. On average, the populations of European

NUTS-2 regions in 2019 were around 1.8 million people, while NUTS-3 populations averaged around 381,000 people in the same year. The standard deviation of nominal GDP per capita across the major European NUTS-2 regions in the year 2019 is 14,559 euro, while the standard deviation of nominal GDP per capita in year 2019 of the NUTS-3 regions is 16,804 euro. Similarly, the standard deviation of yearly nominal GDP per capita growth between the years 2000 and 2019 across European NUTS-2 regions is 2.6 percentage points, versus 3.1 percentage points across the corresponding NUTS-3.[1] Hence, variability of economic activity on the county level exceeds that at the more aggregated level. A major constraint is that Eurostat reports nominal but not real values for the gross domestic product and the gross value is added at the more granular NUTS-3 level. Therefore, research on growth differences between more disaggregated regions, that are more homogeneous amongst themselves, is absent.

While allocation of EU Cohesion Policy funds is at the NUTS-2 level, they are often implemented at the county level. Particularly in Germany, the ”Gemeinschaftsaufgabe Verbesserung der regionalen Wirtschaftsstruktur” (GRW) defines eligible funding areas at the county level, suggesting a mismatch between the granularity of policy implementation and the level of economic analysis. We address this gap by analyzing economic convergence of German counties. In doing so, we provide a more detailed understanding of regional growth dynamics and assess whether convergence patterns observed at the NUTS-2 level persist or diverge on a finer geographical scale. This contributes both to the academic literature on regional convergence and to the policy debate on the effectiveness and targeting of cohesion funds. Empirical work on Europe highlights persistent and increasing regional divergence, and call for a “place-sensitive distributed development” approach that strengthens high-performing areas while designing distinct strategies for less-developed places (Iammarino et al., 2019). Complementing this, the “regional development trap” framework formalizes the idea that regions can become structurally trapped in low growth equilibria, with clear implications for how cohesion and regional policy should be targeted (Diemer et al., 2022). These perspectives reinforce our choice to study economic dynamics at the county (NUTS-3) level: finer geography both exposes intra-regional heterogeneity that is masked at NUTS-2 and helps identify regions that might be entering or escaping development traps, thereby informing the design of place-sensitive policy interventions. Importantly, disparities between urban and rural regions is often masked at the more aggregated NUTS-2 level. Since many NUTS-2 regions encompass both urban and rural areas, they average out important local differences that are crucial for understanding the spatial effectiveness of cohesion policy interventions.

Our contribution to the literature is fourfold. First, we identify convergence patterns at the county level. Second, we analyze the main drivers of growth and how they are asso-

[1] Source: Eurostat, own calculations. Ireland and Belgium are excluded because of data limitations.

ciated with growth differences. We use a rich dataset that encompasses a broader set of indicators commonly employed in the literature (e.g., Bartkowska and Riedl (2012), von Lyncker and Thoennessen (2017)). Third, we provide a comprehensive regional data set for German counties (*Landkreise und kreisfreie Städte*). Fourth, we add to the convergence debate on East German versus West German counties since reunification. In particular, we conduct an extensive analysis of conditional versus club convergence across German counties.

We focus on Germany because its reunification offers an interesting laboratory for the analysis of regional convergence. Despite many formal institutions having converged in Germany, important economic differences remain between the counties. We estimate regional capital stocks and price indices at the county (NUTS-3) level and provide a comprehensive regional data set for all 401 German counties between 2000 and 2019. Due to data availability, we are only able to look at the time from year 2000 onward, so we cannot include the initial years of adjustment in the East German counties. However, as the harmonization of institutions between East and West Germany took place during the 1990's, starting in 2000 allows us to reduce the potential impact of different formal and legal institutional settings.

To analyze club convergence patterns in the German NUTS-3 areas, we employ a regression-based convergence test developed by Phillips and Sul (2007) which has been used to study convergence patterns of house prices, for example Lin and Robberts (2024); Manzi et al. (2023). Although this method, which groups cluster formation factors endogenously, is able to identify clusters, it cannot directly attribute club formation to the conditional or the club convergence hypothesis. Bartkowska and Riedl (2012) have hence proposed a two-step procedure for analyzing the determinants of club formation in an ordered logit regression analysis. We combine the cluster approach with a cross-sectional and dynamic panel analysis of conditional convergence (Barro and Sala-i-Martin, 2004; Caselli et al., 1996). Our results suggest that there has been no conditional convergence, but that heterogeneous clusters of counties have been formed that are converging within themselves, resulting in multiple long-term growth patterns.

We provide a deeper understanding of the channels of development by breaking down the growth contribution of labor into different components. We analyze the effect of interregional net migration on club formation. As migration between counties might play an important role in the growth dynamics of a region, increased labor mobility could determine different convergence results between regional- and national-level studies. We find no evidence of convergence across all counties even if we condition on important drivers of long-term growth such as physical and human capital accumulation. Instead, we identify five convergence clubs, using endogenous clustering. We analyze differences in growth paths and describe the identified clusters based on variations in contributions of capital, labor, and total factor productivity to economic growth. Additionally, we examine the role of migration for regional development and find that net migration has in particular contributed to growth in richer regions.

The paper is structured as follows. First, in Section 2, we describe our data set and estimation methods. In Section 3, we document differences in regional growth contributions, also differentiating between characteristics such as a county being urban or rural. In Section 4, we perform a convergence analysis using cross-sectional and dynamic panel approaches for conditional convergence and club convergence. After finding strong support for the club convergence hypothesis, in Section 5 common factors are recognized as determinants of regional growth for their influence on the formation of the clusters. Finally, we evaluate variations in growth contributions across the different clubs. Finally, in Section 6 we conclude.

2 Data

2.1 Regional Capital Stock and Price Levels

This study uses a regional economic database for Germany, providing comprehensive data on economic accounts and indicators in the 16 federal states (*Länder*) and 401 counties (*Landkreise und kreisfreie Städte*) in Germany (Statistische Ämter des Bundes und der Länder, 2024b,a). At the county level, data for critical variables such as capital stock and price level are not available. To address these gaps, we develop a method to estimate these missing indicators, thereby enhancing the granularity of regional economic data.[2]

A standard growth decomposition into the contributions of capital and labor requires data for the capital stock. However, on the county level in Germany, official data for the capital stock are not available. Therefore, we estimate the capital stock using state-level (NUTS-1) capital intensities in state j for sector k at time t, $\kappa_{j,k,t}$, and sector regional employment shares for each county i: [3]

$$\kappa_{i,t} = \sum_k \kappa_{j,k,t} \times \frac{L_{i,k,t}}{L_{i,t}}. \tag{1}$$

In addition, the total factor productivity (TFP) is given as the Solow residual. In order to compute TFP, we need to specify the labor share, that is, the ratio of labor compensation to GVA.

[2] In contrast to the Annual Regional Database of the European Commission (ARDECO), we use the most recent data vintage of the statistical offices (European Commission, 2024).

[3] Similarly, it is possible to use wages per worker as proxy for the marginal product of labor and estimate the ratio of county-level to state-level capital intensities using the ratio of county-level to state-level wages. However, this approach is more restrictive, as it would be necessary to assume identical productivity and capital shares within states.

Price deflators for regional gross value added are similarly estimated by weighting state-level price deflators with county-level sectoral output shares:

$$P_{i,t} = \sum_k P_{j,k,t} \times \frac{\text{GVA}_{i,k,t}}{\text{GVA}_{i,t}}. \tag{2}$$

Between 2000 and 2019, 33 out of 401 German counties have changed their territorial delineations, which is not accounted for in the data given by the Federal Statistical Office. Therefore, we map the data for these counties back to the NUTS 2021 classification by the European Commission [4] to make those counties comparable over the years.

For a more detailed discussion on how to estimate regional capital stocks, price indices, the labor share, and on the adjustment of data for counties that changed their borders, refer to section A in the Appendix.

2.2 Descriptive Statistics

Important indicators for the level of development can be drawn from arguments of the production function. Table 1 shows the summary statistics for the selected variables in our county-level data set. Statistics are calculated for all 401 counties in the year 2019. They reveal that characteristics across German counties vary substantially. With regard to population, Berlin is, with 3.6 million inhabitants more than a hundred times larger than the smallest county, which is Zweibrücken in Rhineland-Palatinate, with 34,000 inhabitants in 2019. Looking at economic indicators, the real GDP per capita varies between 15,500 euro (Südwestpfalz) and 181,960 euro (Wolfsburg), suggesting that the richest county has GDP per capita values more than ten times higher than in the poorest county.

The lower panel of Table 1 shows summary statistics for specific indicators and their average annual growth rates between 2000 and 2019. Like the levels of those indicators, the average yearly growth rates also show significant variation, with an average GDP per capita growth ranging between −1.2 percent (Offenbach am Main) and 4.3 percent (Ingolstadt). The average population growth rate is negative.

3 Regional growth differences

3.1 Heterogeneous growth contributions

The individual contributions of the 401 German counties to aggregate growth, which amounts to 28 percent between 2000 and 2019, are very different. Figure 1 shows 401

[4] https://ec.europa.eu/eurostat/web/nuts/overview

Table 1: Summary Statistics

	Mean	SD	Min	Max	Units	Obs
			2019			
GDP per capita	36.30	16.19	15.50	181.96	1000 euro p. p.	401
Capital Intensity	416.29	49.08	311.41	531.15	1000 euro p. p.	401
Avg. labor income	41.87	6.05	32.77	78.22	1000 euro p. p.	401
Population	207.40	245.16	34.19	3669.49	1000 persons	401
Participation rate	71.25	19.10	33.71	167.23	percent	401
Unemployment rate	4.69	2.10	1.35	12.83	percent	401
GVA share sector A	1.46	1.46	0.01	7.62	percent	401
GVA share sector BF	32.95	11.10	5.75	80.07	percent	401
GVA share sector GT	65.59	11.32	19.89	94.24	percent	401
Regional price index	108.09	1.10	104.49	110.98		401
Mean annual growth rates between 2000 and 2019						
GDP per capita	1.34	0.67	−1.19	4.27		401
TFP	0.59	0.51	−0.81	3.43		401
Capital intensity	0.83	0.52	−0.26	2.19		401
Avg. labor income	1.91	0.36	0.83	3.15		401
Population	−0.04	0.53	−1.64	1.31		401
Participation rate	0.84	0.44	−0.43	2.31		401
GVA share sector A	0.42	2.72	−5.38	23.76		401
GVA share sector B–F	0.06	0.90	−3.05	3.08		401
GVA share sector G–T	0.11	0.45	−2.60	2.21		401

Note: GDP values per capita are given in 1000 euro per person, capital intensity in 1000 euro per employed person and the average labor income in 1000 euro per employee.
Source: Volkswirtschaftliche Gesamtrechnung der Länder (VGRdL), own calculations.

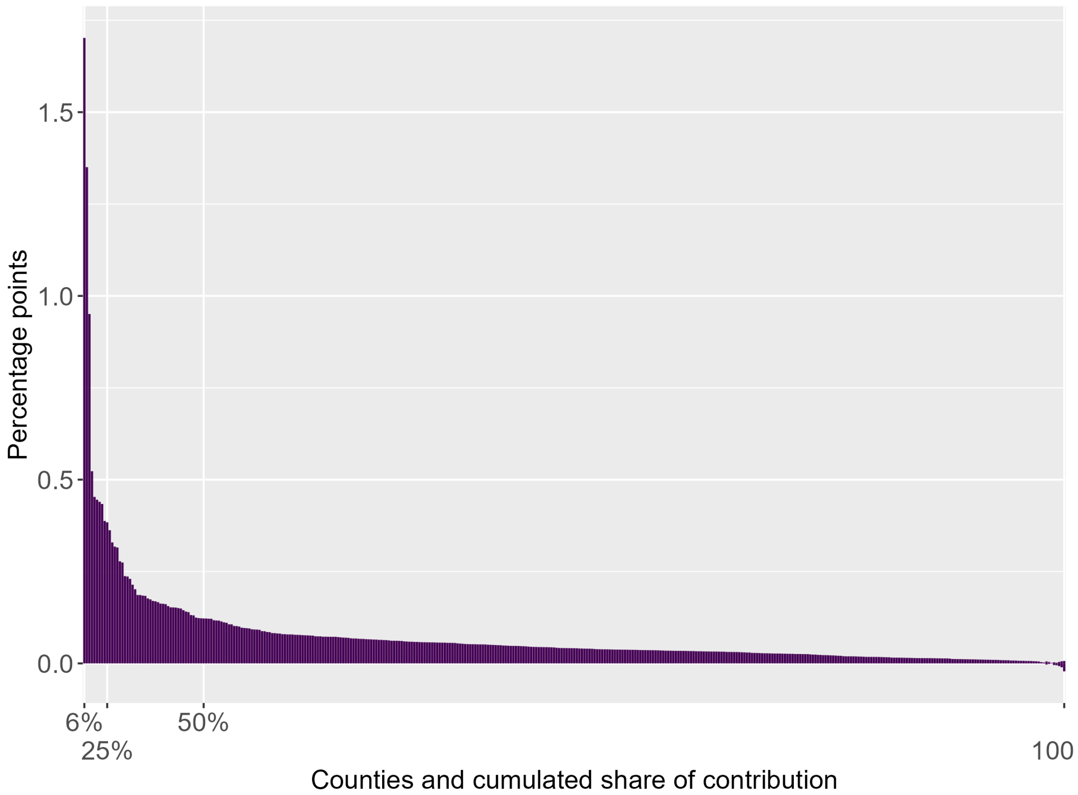
bars, representing growth contributions by county. The horizontal axis shows at which point a certain threshold of cumulated contributions is reached. Berlin is the county with the highest contribution of about 1.7 percent, that is 6 percent of total growth. The ten counties with the highest growth rates account for 25 percent of overall output growth.

Figure 2 shows the growth contributions of each quartile of the output growth distribution of counties. The top 25 percent of counties contribute approximately 13 percentage points (45 percent) to total growth, whereas the fourth quartile contributes only roughly 2 percentage points (eight percent) to the overall increase in output.

Next, we are interested in the specific characteristics of counties that contribute relatively more to growth. We distinguish between rural and urban counties. Our specification uses the classification of urban and rural areas by Eurostat, referring to the NUTS 2021 county borders.[5] Eurostat distinguishes between three different categories; of these, we assign the NUTS intermediate category to our urban category (196 counties). Our results are robust with respect to assigning intermediate counties to the rural category, however, the

[5] https://ec.europa.eu/eurostat/de/web/rural-development/methodology

Figure 1: Contributions to aggregate GVA growth 2000–2019 by county



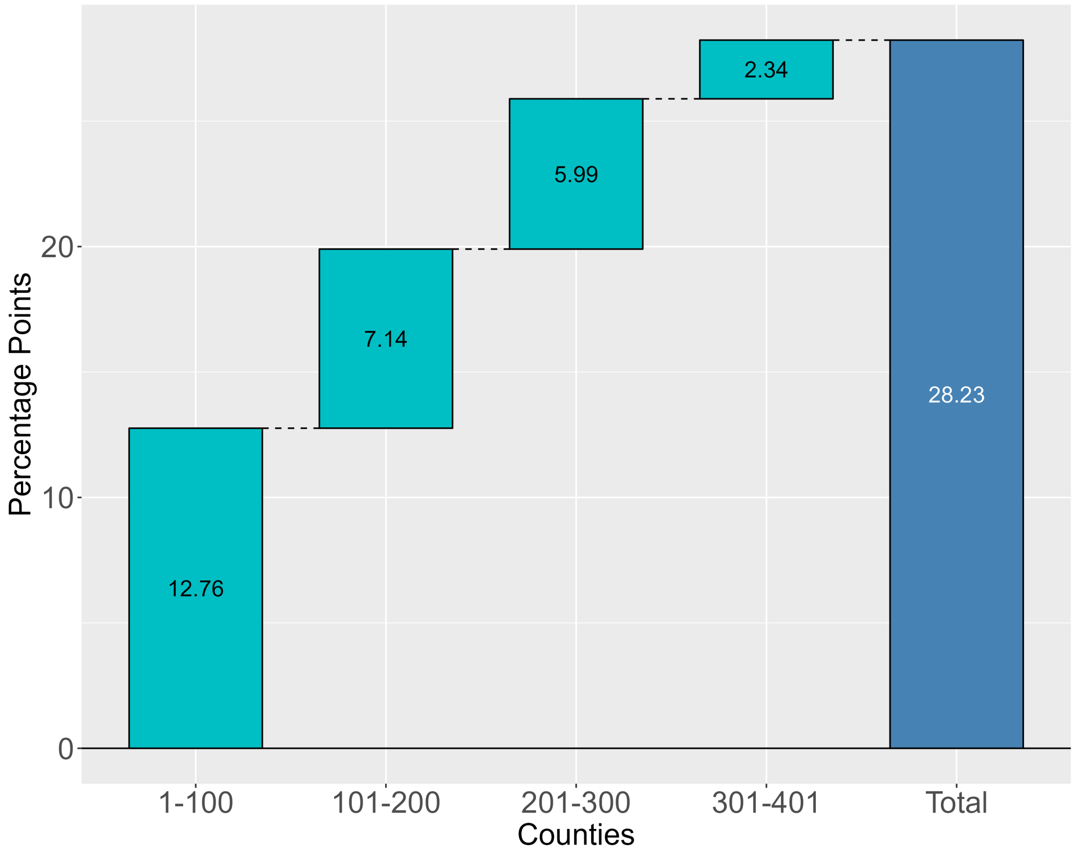
Source: VGRdL, own calculations.

contributions of rural counties are larger in that case. In addition, we distinguish between East and West German counties. 77 percent of counties (309 counties) are located in West Germany, and those counties make up 77 percent of the total population in year 2019. 73 percent of counties (291 counties) are assigned to urban regions, and they make up 84 percent of the German population in year 2019. There are significant differences in the characteristics of the counties and their contributions to overall growth between the years 2000 and 2019 (Figure 3). Urban counties contribute approximately 85 percent to overall growth, whereas rural counties contribute only about 15 percent. Similarly, West German counties account for about 82 percent of the total growth, whereas East German counties contribute around 18 percent. Urban West German areas account for approximately 71 percent, East German urban areas for 16 percent, West German rural counties for eleven percent, and East German rural for two percent of overall output growth.

3.2 Growth Accounting

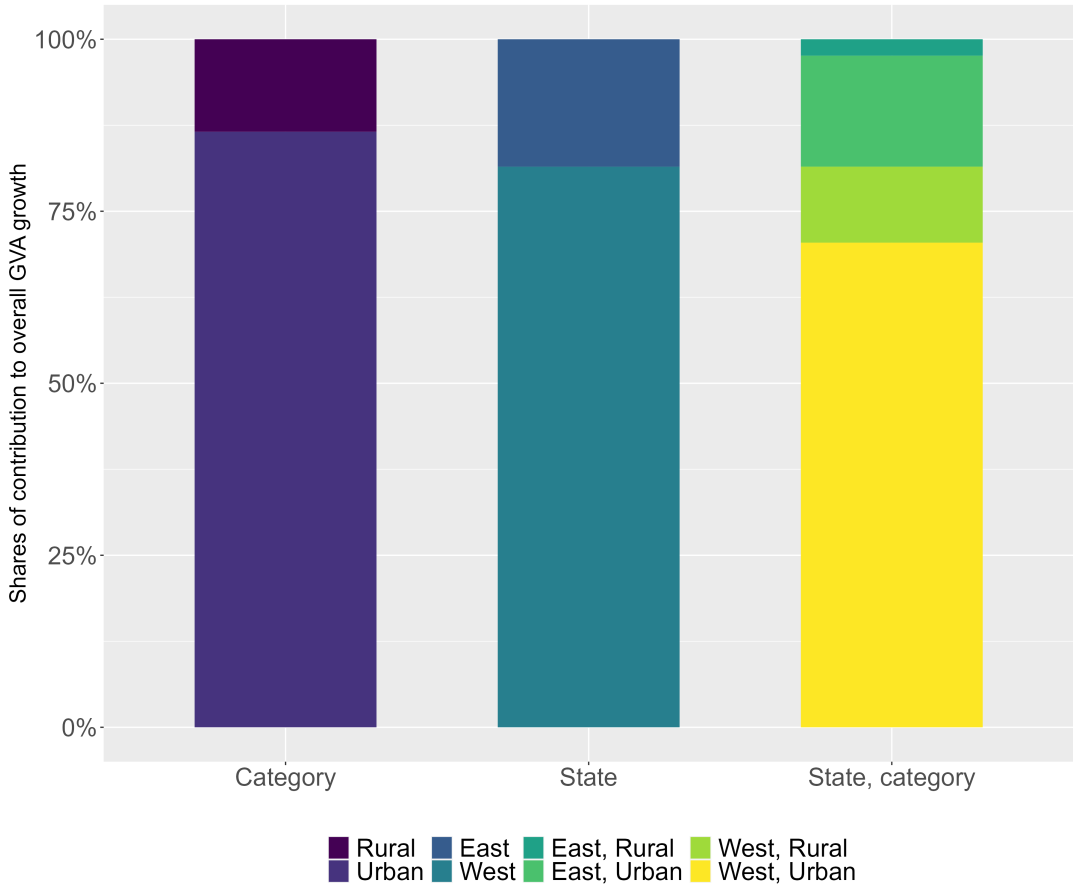
Output growth can be decomposed into the growth contributions of labor, capital, and total factor productivity. We now analyze the extent to which individual counties have contributed to the overall growth in labor, capital, and total factor productivity. We calculate total factor productivity assuming neutral technical change and constant returns to

Figure 2: Contribution of growth quartiles to overall GVA growth, 2000–2019



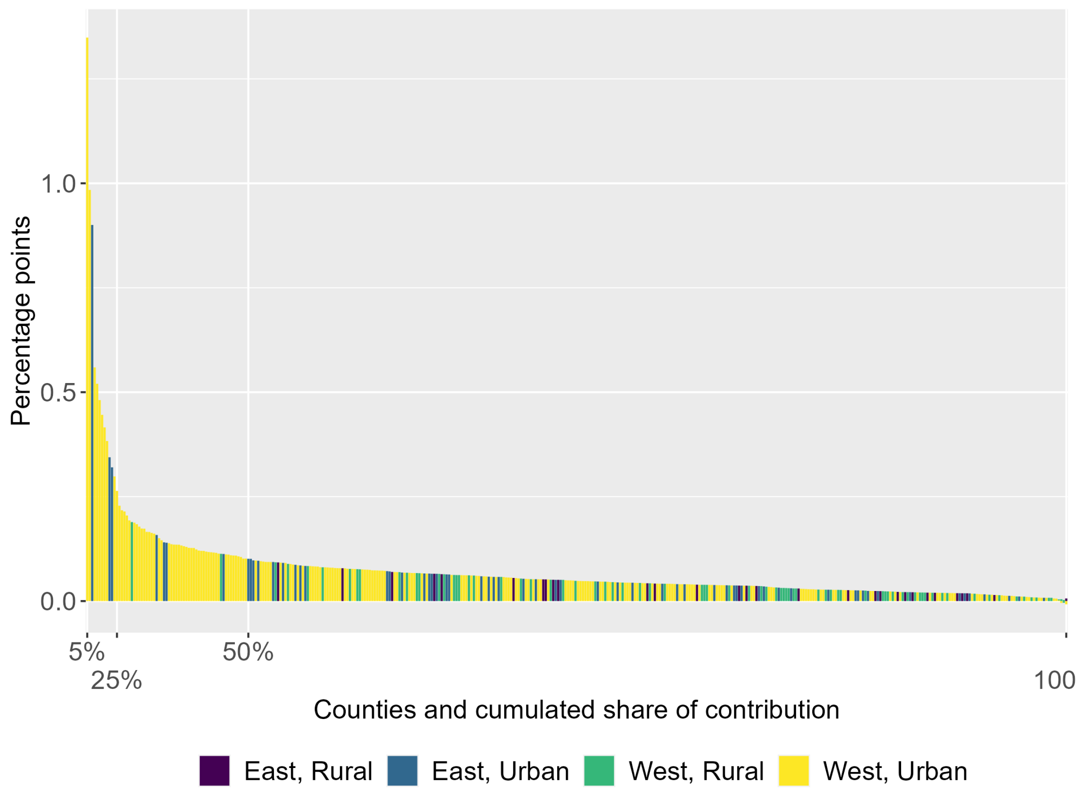
Note: Quartiles are calculated as quartiles of the mean growth of output of each county between 2000–2019. Source: VGRdL, own calculations.

Figure 3: Growth contributions by county groups, 2000–2019



Source: VGRdL, own calculations.

Figure 4: Contributions to aggregate capital growth 2000–2019 by county



Source: VGRdL, own calculations.

scale (Solow, 1957):

$$g_{i,t}^{A} = g_{i,t}^{Y} - \alpha_i g_{i,t}^{K} - (1 - \alpha_i) g_{i,t}^{L}, \tag{3}$$

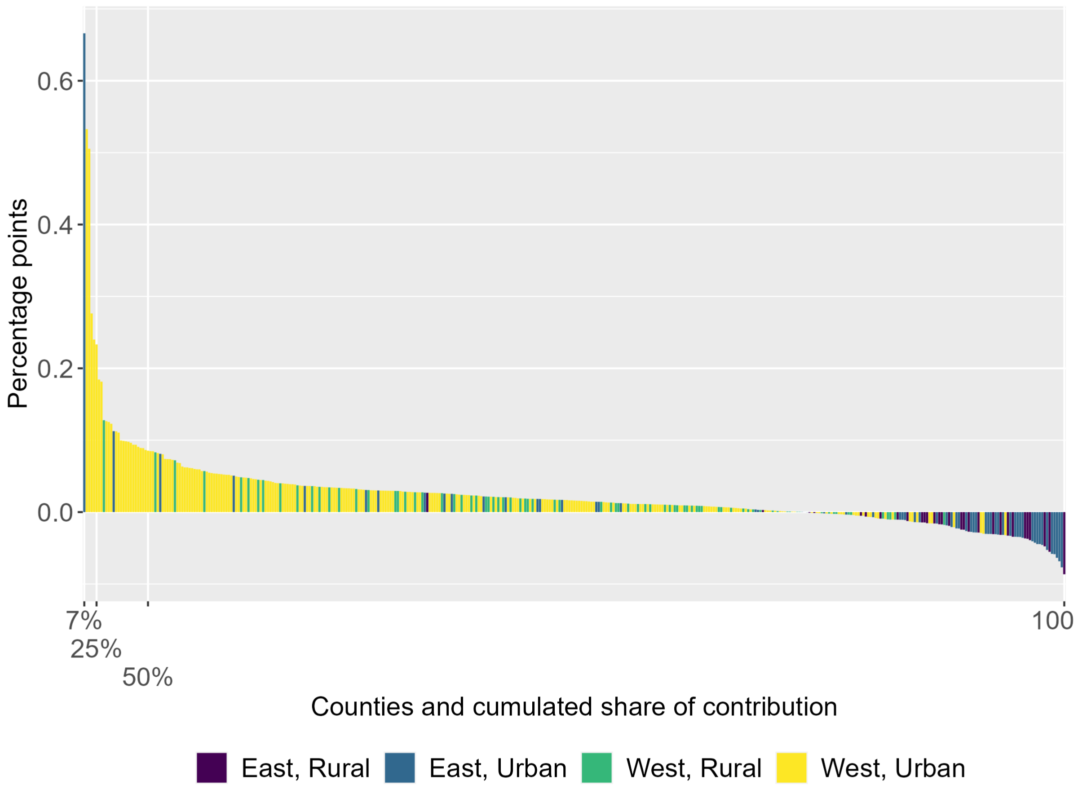
where $g_{i,t}$ is the growth rate of TFP (A), output (Y), capital (K), or labor (L) at time t for county i. Here, α_i is the mean capital share and is calculated with the adjusted labor income $\widetilde{LAB}$, that is the product of the labor income times the ratio of employed persons (EP) to employees (EE), in order to account for the income of self-employed persons:

$$\alpha_i = \frac{1}{T} \sum_{t}^{T} \left(1 - \frac{\widetilde{LAB}_{i,t}}{Y_{i,t}} \right), \qquad \widetilde{LAB}_{i,t} = LAB_{i,t} \frac{EP_{i,t}}{EE_{i,t}}. \tag{4}$$

Figure 4 now shows each county's contribution to the aggregate growth of capital. The bars are highlighted in different colors according to the counties' affiliation to East or West Germany, and to urban or rural areas. The county with the highest capital contribution—of about 1.3 percentage points—is the city of Munich, which provides five percent to the total increase in capital. Three percent of counties are contributing 25 percent to overall growth and 66 of 401 counties are contributing half of the increase of capital. The urban counties of West Germany exhibit the highest capital contributions.

Next, figure 5 shows each county's contribution to the overall growth in labor. The city of Berlin has, with a contribution of 0.7 percentage points, the highest share in overall

Figure 5: Contribution to aggregate labor growth 2000–2019 by county



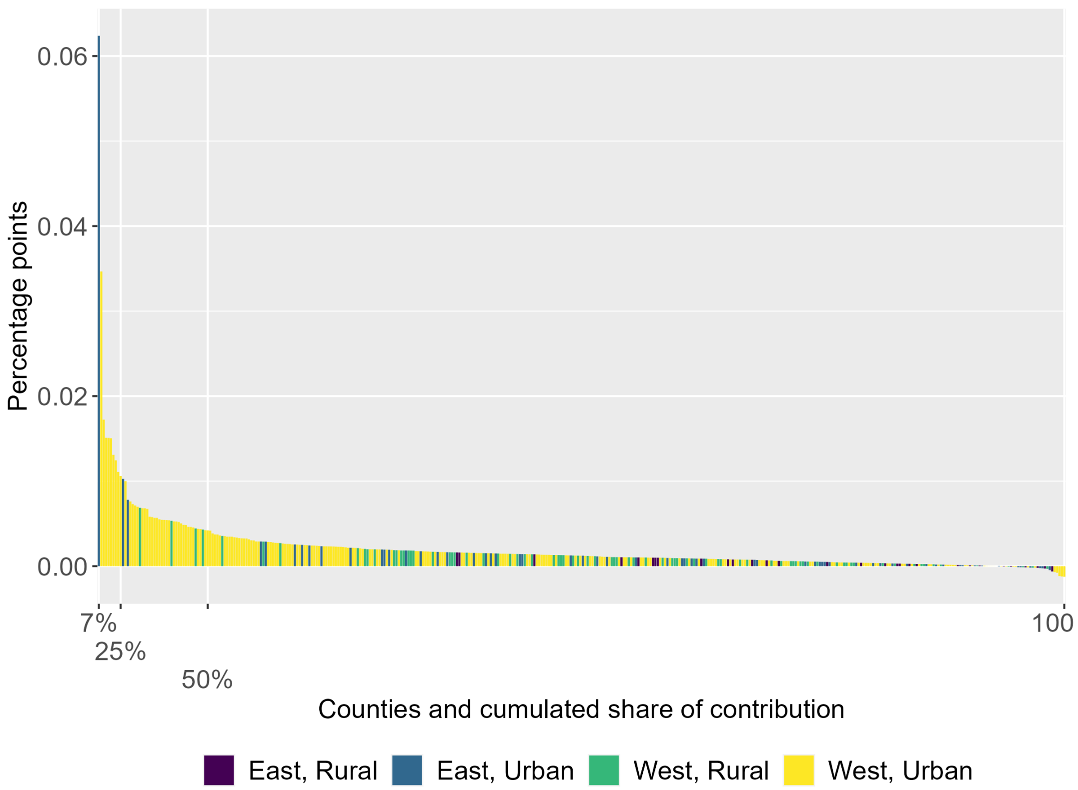
Source: VGRdL, own calculations.

labor growth. Contributions to labor growth are especially unbalanced. Six out of 401 counties contribute 25 percent and six percent of counties are contributing 50 percent to the overall increase in labor during the years 2000 and 2019. A significant share of counties has experienced negative growth in labor relative to the base year, and thus are contributing adversely to the aggregate growth of labor. Notably, counties that have experienced negative labor growth belong, to a large extent, to urban and rural areas in East Germany, whereas the large positive labor contributions are located mostly in urban areas in West Germany. This is in line with demographic change in East Germany and worker emigration during the last two decades.

In figure 6 we measure each county's contribution to national TFP growth by weighting regional productivity growth with the lagged share of that county's output to national output, and take averages over the entire period. The results indicate that 11 percent of counties contribute about 50 percent to overall productivity growth. Most of these highly contributing counties belong to urban counties in West Germany, except for the cities Berlin, Leipzig, and Dresden, which are urban counties in East Germany.

Next, we decompose the output growth of each quartile of the mean output growth distribution into its different contributors, capital, labor, and TFP. For the decomposition on the aggregated level, we use each county's yearly growth rates of capital K, labor L, and

Figure 6: Contribution to aggregate TFP growth 2000–2019 by county



Source: VGRdL, own calculations. Note: Contributions of TFP are calculated as yearly regional growth rates, weighted by the lagged share of regional to national GVA. Then, averages are taken over the considered period.

TFP A, multiplied with their regional capital shares α, and weight them by the share of regional GVA Y_i to the GVA of each quartile Y^Q. Summing over all counties, we obtain the yearly contributions of each quartile Q, that are then averaged over our sample period:

$$Y_t^Q = \sum_{i \in Q} Y_{i,t} \tag{5}$$

$$1 + g_t^Q = \frac{Y_t^Q}{Y_{t-1}^Q} = \frac{\sum_i Y_{i,t} \times \frac{Y_{i,t-1}}{Y_{i,t-1}}}{Y_{t-1}^Q} = \sum_i (1 + g_{i,t}) \times \frac{Y_{i,t-1}}{Y_{t-1}^Q} \tag{6}$$

$$g_t^Q = \sum_i \frac{Y_{i,t-1}}{Y_{t-1}^Q} \times g_{i,t} = \sum_i \frac{Y_{i,t-1}}{Y_{t-1}^Q} \left(g_{it}^A + \alpha_i g_{i,t}^K + (1 - \alpha_i) g_{i,t}^L \right) \tag{7}$$

$$g^Q = \left(\frac{1}{T} \right) \sum_t^T g_t^Q \tag{8}$$

We decompose labor into its components, viz., the average working hours of the employed persons, the participation rate, and the working age population:

$$Y_{i,t} = A_{i,t} F(K_{i,t}, L_{i,t}) = A_{i,t} F\left(K_{i,t}, \frac{L_{i,t}}{EP_{i,t}} \times \frac{EP_{i,t}}{N_{i,t}} \times N_{i,t} \right), \tag{9}$$

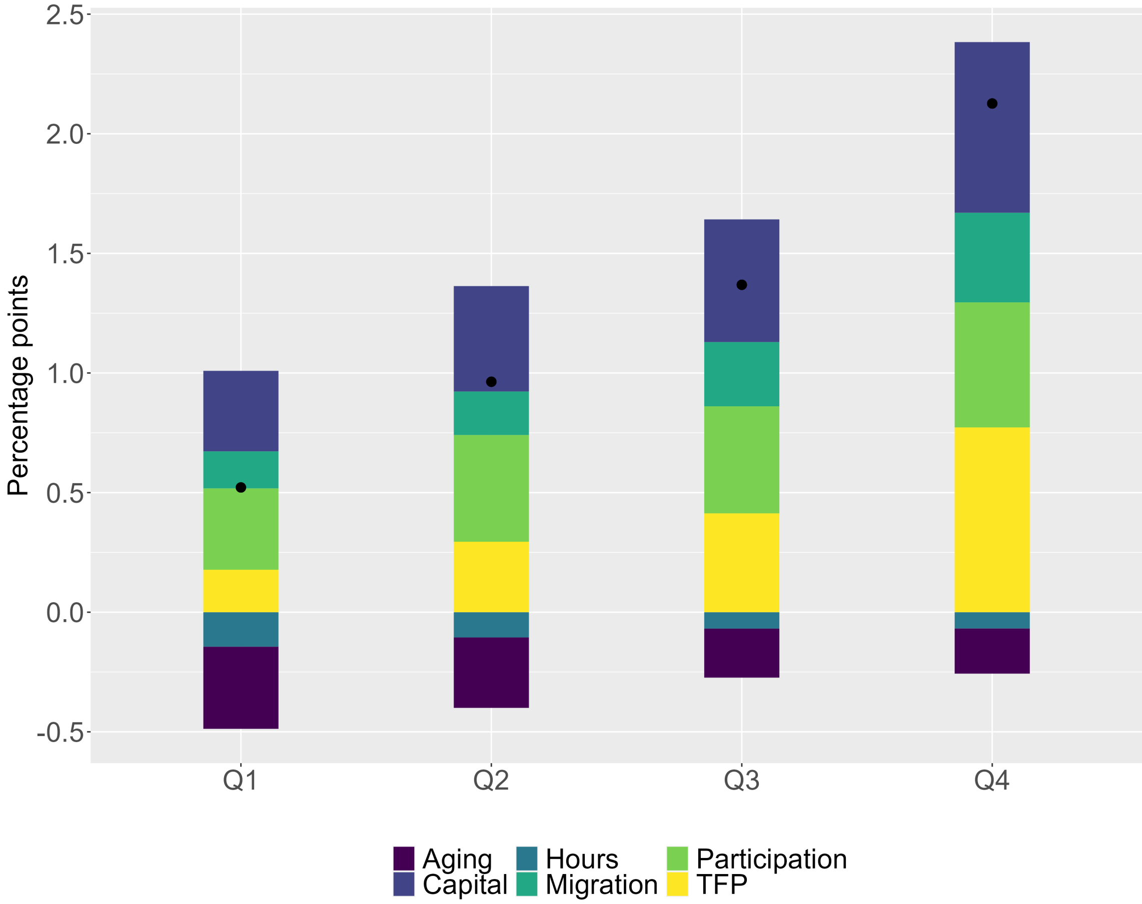
where L refers to hours worked, EP to employed persons, and N to the working-age population.

In order to the analyze effects of inter-regional net migration on development of those counties, we break down the working age population into entries, exits and net migration. Because regional data for net migration are not broken down into the age group of people between 15 and 74 years old, the values in equation 10 for net migration are the differences between the working age population in each county between two given periods, minus the lagged data of entries into the working age population (people aged 14), plus the lagged exits from this group (people that aged 74), deaths in the working age group, and deaths of people aged 14, all in the preceding period.

$$N_{i,t} = \sum_{a=15}^{74} Pop_{i,a,t} = \sum_{a=15}^{74} Pop_{i,a-1,t-1} - \sum_{a=15}^{74} deaths_{i,a-1,t-1} + netmig_{i,a,t-1}, \tag{10}$$

where i is the county indicator, t represents each year, and a refers to the age. Because, on the regional level, death numbers are only available for certain age groups, we have to approximate the number of people who died at age 14 using the national share of deaths of people aged 14 out of a broad age group covering 1 to 14 years. Hence, we multiply the regional numbers of deaths in the group of persons aged 1–14 years with the national share of people aged 14 of this age group. Detailed age data for population are only available since 2003, so, for the years before that, we use national shares of people aged 14 and 74 of the respective age group in order to calculate the number of entries and exits

Figure 7: Growth decomposition by quartile of mean output growth, 2002–2019



Source: VGRdL, own calculations.

into and from the working age group.

Figure 7 shows the results of this decomposition. Quartile one refers to the 25 percent of counties that have, on average, been growing the least in the considered period. The capital contribution increases steadily with the growth quartiles, while the contribution of TFP is similar for quartiles 1 and 2, but then significantly higher in quartiles 3 and 4. Looking at the decomposition of the factor labor, we see large negative effects of aging throughout all quartiles and a less severe but still negative contribution of the average hours worked per employed person. Although the contribution of the change in the participation rate is relatively stable between quartiles, the contribution of net migration varies.

Overall, we can identify differences in growth across counties that are related to differences in input factors. Especially unevenly distributed are contributions of the factor labor.

4 Regional Convergence

4.1 β-Convergence

In order to analyze conditional convergence across German counties, we use two distinct approaches. First, we use a cross-section approach based on the empirical specification by Barro and Sala-i-Martin (2004), which is derived from the Solow model (Solow, 1956). The dependent variable is the logarithmic difference in real GVA per working age population ($y = \frac{Y}{N}$, where the working age is defined as 15 to 74 years) of county i over the period of interest, that is, between the year 2000 and 2019. We use GVA per working age population to control for different demographic structures across counties. On the right-hand side, next to the initial GVA per working age population value of year 2000, are the averages of specific control variables:

$$\ln\left(\frac{y_{it}}{y_{it_0}}\right) = a_0 + \beta \ln(y_{i,t_0}) + a_1 \ln(s) + a_2 \ln(n) + a_3 \ln(school) + \varepsilon_i \tag{11}$$

where s is the proportion of real investment to GDP as in Mankiw et al. (1992), and n represents the birthrate. Barro and Sala-i-Martin (2004) use fertility rates but, due to data limitations, we use the number of births per inhabitant. Likewise, to estimate the regional capital stock, county-specific depreciation rates are calculated as a sum over sector-specific state-level depreciation rates multiplied with the estimates of regional sectoral capital as share of total regional capital:

$$\delta_i = \frac{1}{T}\sum_t^T \delta_{i,t} = \frac{1}{T}\sum_t^T \sum_k \delta_{j,k,t} \times \frac{K_{j,k,t}}{L_{j,k,t}} \times \frac{L_{i,k,t}}{\sum_k \frac{K_{j,k,t}}{L_{j,k,t}} \times L_{i,k,t}} \tag{12}$$

Regional investments correspond to the change in the capital stock plus the depreciated capital stock:

$$I_{i,t} = K_{i,t} - (1 - \delta_i)K_{i,t-1}. \tag{13}$$

We also add a measure for human capital to the regression (*school*), which is given by the average share of high school graduates (Mankiw et al., 1992).

The results of the regression analysis are given in the first column of the Table 2.

The investment rate is significantly positively associated with the average growth rate, whereas the population growth indicator (the birth rate) is significantly negatively related to the dependent variable. The results are in line with those obtained by Barro and Sala-i-Martin (2004). The coefficient on initial GVA per working age person is insignificant when applied to our regional data set for Germany. It is also ten times smaller in

Table 2: Conditional β-Convergence

	Dependent variable:		
	$\frac{1}{t-t_0}\ln\left(\frac{y_{i,t}}{y_{i,t_0}}\right)$		
	OLS	Diff GMM	System GMM
	(1)	(2)	(3)
$\ln(y_{i,t_0})$	-0.003	0.021	0.006
	(0.002)	(0.084)	(0.031)
$\ln(I/GDP)$	0.008^{***}	-0.0005	0.053^{***}
	(0.001)	(0.002)	(0.013)
$\ln(n)$	-0.015^{***}	-0.002	-0.053^{**}
	(0.005)	(0.013)	(0.023)
$\ln(school)$	0.003^{**}	0.001	0.028^{***}
	(0.001)	(0.003)	(0.006)
Observations	401	2406	2406
R^2	0.214	-	-
Adjusted R^2	0.206	-	-
AC test (2)	-	0.17	0.58
Sargan test	-	0.07	0.003
Diff Sargan	-	-	0.007

Note: *p<0.1; **p<0.05; ***p<0.01. Robust SEs in parentheses.

t_0 in OLS refers to the year 2000.

t_0 in GMM refers to the lagged period of t, where each t is a three-year average.

magnitude than the convergence rates found in several country-level studies, such as, for example, in Barro and Sala-i-Martin (2004) or Mankiw et al. (1992).

Although the cross-country approach is specifically useful in the growth context, as it allows for an analysis without a steady-state assumption, equation 11 introduces an estimation bias if the individual effect is correlated with other variables on the right-hand side (Caselli et al., 1996). There can be scenarios in which the region-specific productivity shock ε_i is correlated with the saving and population growth rate, since the initial endowment of technology of a region includes general characteristics such as institutions, climate, etc. This would bias the OLS estimates, which are only consistent under the assumption of no correlation.

Therefore, we refer to another strand of the literature on growth convergence and apply a dynamic panel setting to our analysis. The structure of panel data can help to address violations of exogenous regressor assumption, as individual effects can be eliminated through first-difference transformations. Specifically, we adopt the first-difference generalized method of moments (GMM) estimator, proposed by Holtz-Eakin et al. (1988) and Arellano and Bond (1991). In the growth literature, it was introduced by Caselli et al. (1996). Reformulating equation (11) transforms the cross-country setting into a dynamic AR (1) equation:

$$\ln y_{i,t} - \ln(y_{i,t-\tau}) = \beta \ln(y_{i,t-\tau}) + a_1 \ln(s_{i,t-\tau}) + a_2 \ln(n_{i,t-\tau}) + a_3 \ln(school_{i,t-\tau}) + \mu_i + \eta_t + \varepsilon_{i,t} \quad (14)$$

Again, the applied control variables are measured as period-specific means. In this specification, it is necessary that there is no serial correlation of order τ (that is, $E[\varepsilon_{i,t}\varepsilon_{i,t-\tau}] = 0$ (Caselli et al., 1996). We use 3-year intervals, so $\tau = 3$. Performing a test of autocorrelation based on the residuals of the estimation following Arellano and Bond (1991), we cannot reject the null hypothesis of no autocorrelation. Based on the Sargan test of overidentifying restrictions, we cannot reject the null hypothesis that our instruments are valid at the five percent significance level.

Importantly, the assumption that the error term $\varepsilon_{i,t}$ is serially uncorrelated and that the explanatory variables are predetermined implies moment conditions that can be used in the context of GMM: Predetermined variables allow for a feedback process of the lagged dependent variable on current growth determinants (Moral-Benito, 2010). Those conditions can thus be interpreted as an instrumental-variable model with lagged levels used as instruments for the first differences. Following Arellano and Bond (1991), we use y as an instrument in the difference-GMM estimation.

In a robustness check, we employ the system-GMM approach introduced by Arellano and Bover (1995), which uses lagged differences as further instruments to address potential weaknesses in the difference-GMM setup. Yet, the inclusion of these extra instruments raises the risk of overfitting, particularly in short panels like the one under study. In line with Blundell and Bond (1998), we extend the instrument set in our system-GMM estimation by including all variables from the regression equation, in addition to y. The autocorrelation test of order two indicates no residual autocorrelation. However, both the Sargan test and the difference Sargan test suggest that the additional instruments used in the system-GMM estimation are not valid when compared to those in the difference-GMM estimation.

Columns two and three in Table 2 report the results for the difference-GMM estimator and the system-GMM estimator. All coefficients of the difference-GMM estimation are insignificant, the coefficients of the system-GMM estimation are in line with those of the OLS regression. Importantly, in both dynamic panel specifications, the β coefficient on the initial GVA per working age population is insignificant, thus indicating that there has been only limited convergence across German counties between the years 2000 and 2019.

4.2 Regional Convergence Clubs

The previous section has shown that there is no conditional convergence among German counties, if we control only for investment ratio, birth rate and human capital formation. In this section, we apply an alternative technique to identify convergence clubs. Identifying these clubs a priori can lead to somewhat deliberate results if the grouping relies on deterministic variables and their thresholds (Bartkowska and Riedl, 2012). Phillips and Sul (2007) developed a clustering method in which grouping factors are left unspecified so that data-driven club formation occurs endogenously. Their approach is formulated as nonlinear time-varying factor model that allows for individual and transitional heterogeneity. For our analysis, we apply the log-t test, which represents a modification of the usual panel data decomposition.

First, the transition path of log per-capita output is given as:

$$\ln y_{it} = \ln \tilde{y}_i^* + \ln A_{i0} + [\ln \tilde{y}_{i0} - \ln \tilde{y}_i^*]\, e^{-\beta_{it} t} + x_{it} t = a_{it} + x_{it} t, \tag{15}$$

where $\tilde{y}_{i0}$ and $\tilde{y}_i^*$ describe initial and steady-state levels of per capita output, and the time-varying technology level follows a growth path given by $A_{it} = A_{i0} \exp(x_{it} t)$, governed by the technological progress parameter x_{it}. For $t \to \infty$, long-run paths of $\log y_{it}$ are determined by x_{it}.

Equation (15) can be reformulated:

$$\ln y_{it} = \left(\frac{a_{it} + x_{it} t}{\mu_t} \right) \mu_t = b_{it} \mu_t, \tag{16}$$

with b_{it} representing the weight of each region on the common trend μ_t and thus representing the individual transition to the average steady state growth path. Using b_{it}, the relative time-varying transition trajectory of region i can be modeled:

$$h_{it} = \frac{\ln y_{it}}{N^{-1}\sum_{i=1}^{N}\ln y_{it}} = \frac{b_{it}}{N^{-1}\sum_{i=1}^{N} b_{it}}, \tag{17}$$

which corresponds to the individual's path relative to the cross-section average.

The transition coefficients are specified so as to allow for heterogeneity across time and individuals:

$$b_{it} = b_i + \frac{\sigma_i \phi_{it}}{L(t)t^{\alpha}}, \tag{18}$$

where b_i is fixed, ϕ_{it} is i.i.d. $N(0,1)$, and $L(t) \to \infty$ as $t \to \infty$. Then, the null hypothesis of convergence is formulated as

$$H_0:\ b_i = b \ \&\ \alpha \geq 0. \tag{19}$$

Finally, using $H_t = N^{-1}\sum_{i=1}^{N}(h_{it}-1)^2$, $h_{it} = \log y_{it}/(N^{-1}\sum_{i=1}^{N}\log y_{it})$, and setting $L(t) = \ln t$, the following equation can be used to test convergence through OLS estimation:

$$\ln\frac{H_1}{H_t} - 2\ln(\ln t) = a + \underbrace{\beta}_{=2\alpha}\ln t + u_t, \text{ for } t = [r\mathrm{T}], [r\mathrm{T}+1], \ldots, T. \tag{20}$$

Here, H_1/H_t is the cross-sectional variance ratio, β is the speed-of-convergence parameter, $-2\ln(\ln t)$ is a penalization function, and r takes values in the interval $(0,1]$ and represents a parameter that ignores the first few observations from the estimation. After having conducted Monte Carlo simulations, Phillips and Sul (2007) suggest setting r equal to a third of the number of observations for sample sizes with $T < 50$, which we adapt for our analysis. We test the null hypothesis of convergence through a one-sided t-test robust to heteroskedasticity and autocorrelation (HAC) $\beta > 0$ for a 5% significance level, such that we reject the null hypothesis if $t_{\hat{\beta}} < -1.65$. After rejecting the test for the sample as a whole, a four-step testing procedure is performed on subgroups of the sample.

First, counties are sorted in descending order for the last observed year. Then, the log-t test is applied to the next $k > 2$ units, such that the group size k^* corresponds to:

$$k^* = \arg\max_k \{t_k\} \text{ subject to } \min\{t_k\} > -1.65. \tag{21}$$

After the group of k^* units is detected, the log-t test is applied to all remaining units, one by one , to test for convergence. If no convergence can be detected, the first three steps are applied to the remaining units to check if other clubs exist. If no clubs are found, these units diverge.

Table 3: Convergence club classification

	# of units	$\hat{b}$	SE ($\hat{b}$)	t-statistic	Avg. Y/L
Club 0	1	-	-	-	144.64
Club 1	2	−1.718	3.103	−0.554	114.09
Club 2	11	0.183	0.048	3.804	82.51
Club 3	51	−0.033	0.056	−0.581	55.06
Club 4	144	0.209	0.057	3.645	38.42
Club 5	192	−0.046	0.043	−1.077	28.91

Note: Club 0 indicates the diverging county in the sample.

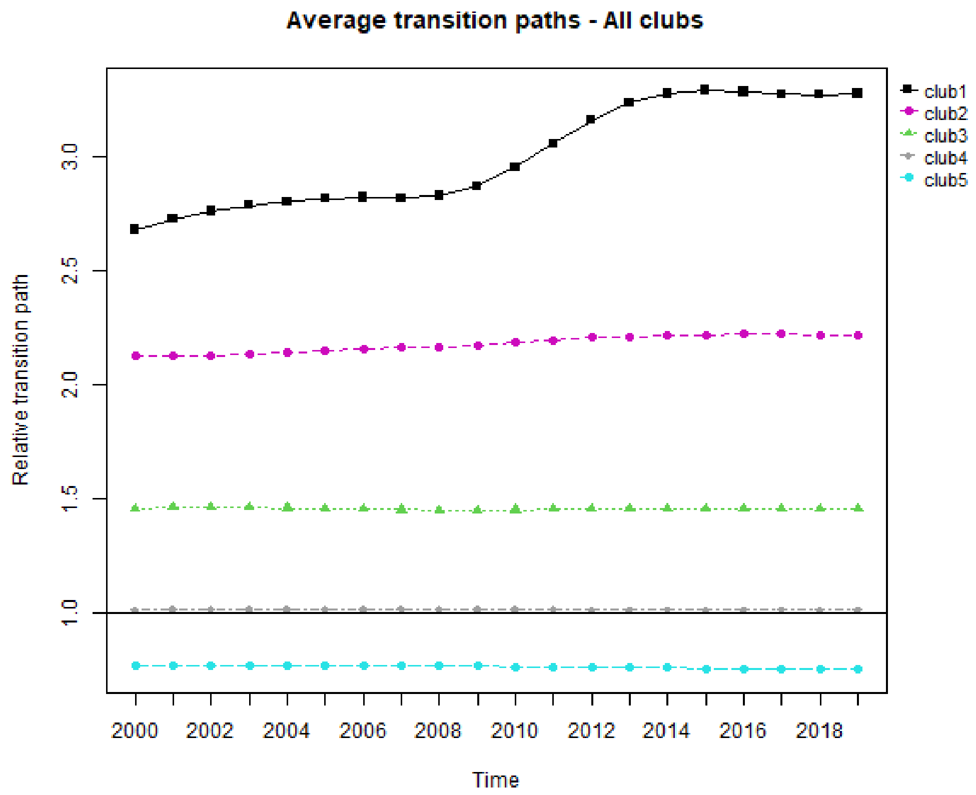
Following Phillips and Sul (2007), we apply the Hodrick-Prescott (HP) filter to our GVA series to abstract from business cycle movements (Hodrick and Prescott, 1997). The smoothing parameter λ is chosen to equal 6.25, according to the proposition of Ravn and Uhlig (2002) for data with annual frequency.

Applying the log-t test to our sample of 401 German counties over the years 2000–2019 rejects the hypothesis of general convergence at the five-percent significance level. This again confirms our previous findings that there has been no convergence of counties to the same long-run steady state paths of GVA per working age population. We identify nine clubs and one divergent region. Because the number of identified clubs is strongly based on the formation of the core group, we test the overdetermination of adjacent clubs with the merging algorithm proposed by Phillips and Sul (2009).

A complete list of all final clubs and their respective counties is given in Table B.1 in the appendix. The results of the log-t test procedures are presented in Table 3. The algorithms identify five clubs in total, and one diverging unit "Club 0", the city of Wolfsburg. Most of the counties are included in Clubs 4 and 5, whereas the first two clubs only include 13 counties. The average GVA per working age population of each club further shows that Clubs 1–3 are way above the average GVA per working age population on a national level, which amounts up to 37.8 thousand euro across all counties and years. Output in Club 5, which makes up almost half of total German counties, is with an average of 28.9 thousand euro per working age person, much lower than the national mean value.

Looking at the magnitude of $\hat{b}$, we can identify the type of convergence. The point estimates for Clubs 2 and 4 are both significantly positive, but less than two (that is, $\alpha < 1$). This indicates that the hypothesis of absolute level convergence is rejected, but that the club members converge relatively, suggesting convergence of growth rates over time. Clubs 1, 3, and 5 show negative but insignificant $\hat{b}$ estimates, which was interpreted by Phillips and Sul (2009) as some form of slower relative convergence, compared to those of other clubs.

Figure 8: Transition paths across clubs



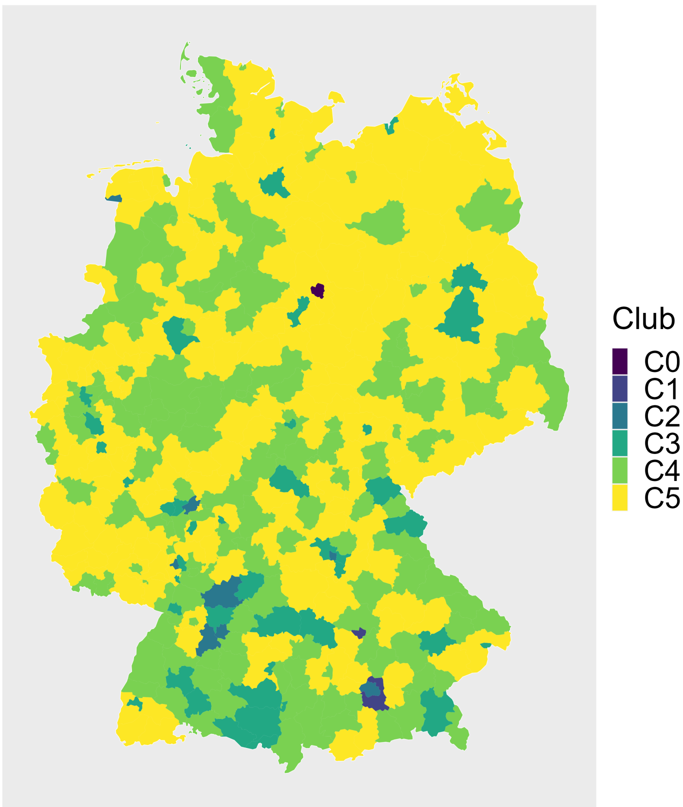
Furthermore, figure 8 shows the transitional behavior of each club to their respective steady state, averaged across each individual trajectory h_{it} in equation 17. Because Club 1 consists of only two counties, its average transition path is rather uneven, whereas paths of the other clubs are much smoother. Evidently, Club 1's transition course is based on individual output trajectories that are generally three times larger than the average growth components across all German counties. Also, figure 8 shows relative increases in the transition parameters of Club 1 compared to steady state paths of all other clubs after the global financial crisis until year 2015. Club 5, our largest cluster in terms of the number of counties, is constantly below the average transition path across all NUTS 3 counties in Germany. Hence, our results suggest that we cannot detect level convergence, but we do find a relatively stronger or weaker convergence of growth rates within the identified clubs.

Counties selected in different clubs share common characteristics (see Table 4). Figure 9 plots the spatial concentration of the identified clusters. Here, Club 0 represents the city of Wolfsburg as a divergent unit that does not belong to any of the clubs. It becomes apparent that the higher output Clubs 1–3 are mostly located in the south of Germany, whereas the counties of Club 5 are mostly located in East Germany.

Table 4: Clubs and keywords

Club 1	Automotive Powerhouse and Bavarian Silicon Valley: Economic Dominance of Ingolstadt and Munich (County)
Club 2	Urban Economic Giants
Club 3	Innovation and Industry Synergy
Club 4	Cultural Heritage in southern Germany meets former mining areas in West Germany
Club 5	Rural areas, periphery, and East German counties

Figure 9: Convergence club membership by county



A Moran's I analysis reveals that the spatial autocorrelation of counties that are assigned to similar clubs is low. Using a contiguous neighbor definition, we determine polygons with at least one shared vertex as neighboring counties where weights are assigned equally among the number of identified neighbors. The Moran coefficient I has a value of 0.05, indicating a positive but weak association between each county's identified club and the weighted average of geographical neighbors' club membership.

Lastly, to account for potential interdependencies between counties that might be linked through commuter flows across communities, we conduct the club convergence analysis for labor market regions, which are predefined clusters of counties reflecting spatial aspects of economic activity and are issued by the Institute for Employment Research (IAB). The borders of these clusters are therefore not politically determined, and labor market regions are much larger than counties.[6] Figures C.1 and C.3 in the Appendix show the results from using the log-t test on labor market regions, and Table C.1 lists the labor market regions with the corresponding club names. Obviously, a lot of the regional heterogeneity gets lost with aggregation to larger entities. Still, counties in the southern and southwestern parts of Germany, as well as the areas around Wolfsburg and Berlin, belong to the higher developed clusters, whereas counties from central and East Germany, as well as some counties in Saarland and Rhineland-Palatinate, belong to lower developed clubs. As labor market areas are themselves predetermined clusters, we stick to the county level as the main unit of analysis when employing the clustering algorithms on geographical regions.

5 Determinants of convergence club membership

5.1 Explanatory variables and theoretical background

The analysis has shown that there has been no convergence across counties in Germany between the years 2000 and 2019, but that counties belong to five different growth clusters. Now, we want to shed light on the factors that influence probabilities of club membership. Although conditional convergence theories suggest that regions that are similar in their fundamentals converge to the same equilibrium regardless of their initial conditions, the club convergence analysis has emphasized the importance of initial per capita output levels to the evolution of long-run growth paths. In addition, geographic indicators might play a role in club formation. Thus, we employ initial values for the production factors, structural characteristics, and geographic controls as right-hand side variables of

[6] There are 50 labor market regions vs. 401 counties. For more information, see: https://statistik.arbeitsagentur.de/DE/Navigation/Grundlagen/Klassifikationen/Regionale-Gliederungen/Weitere-Gebietsgliederungen-Nav.html

the regression equation to isolate effects. Importantly, the existence of different clubs is permitted through differences in initial output, which is given here as real GVA per working age person. Our control variables mostly conform to those of Mora (2008), however, we extend the list of regressors by certain geographic and structural controls that are in line with neoclassical, as well as with new economic geography (NEG) theories.

In the neoclassical growth theory (Solow, 1956), the emergence of multiple steady state equilibria is explained through differences in factor endowments. To account for differences in labor forces, we employ the participation rate, which is given as the ratio between workers and the working age population, as a labor market indicator. Heterogeneity between individuals can allow the intensity of capital to influence multiple steady states through differences in saving rates (Galor, 1996), which is why the investment rate in physical capital serves as another control for the determination of the club. As human capital is an important factor in the augmented Solow growth model and, as noted in Quah (1996), it is a factor that conditioning the presence of regional coalitions, we include the share of high school students as a proxy.

In addition, we control for the regional sectoral composition using the share of the manufacturing sector and construct a measure of sectoral specialization, which is given by the manufacturing (C) and information technology (K-N) share, as a proxy for more refined activities that require a certain level of industry development. As noted in Aghion and Howitt (1992), innovations can foster monopolistic power in firms, which guarantees market returns and gives firms incentives to invest in the knowledge sector. In the long run, differences in income levels will then be determined by differences in technology endowments. Here, we employ the average share of workers in the research and development (R&D) sector as proxy for the innovative capacity of each region.[7] We also use the share of business registrations and deregistrations as a proxy for regional firm-level competition. Next, demographic indicators might be responsible for differences in growth dynamics. In neoclassical models, the population growth rate is a factor that influences growth, which we include here as average over the years 1995 to 2000. We further use the share of persons aged above 75 as a control for counties with relatively high shares of people above the working age in the year 2000.

Finally, the NEG literature suggests that endogenous development is conveyed through the spatial concentration of economic activity (Krugman and Venables, 1996). Agglomeration related to labor market pooling can promote benefits related to financial externalities, which is why we use population density as a control. Related, differences in economic development can be historically determined through a county being classified as more urban vs. more rural, so we use a dummy for a county being urban. Lastly, through

[7] Data on the county level is only available since 2008, which is why we take the regional average over the entire sample period as proxy.

Table 5: Right-hand side variables

Indicator	Variable	Time period
	Production function indicators	
Output per capita	GVA per working age person	logs, 2000
Labor market	Participation rate	2000
Investment rate	Share of Investment of GDP	2000
Human capital	Share of Students with high school diploma of total degrees	2000
	Structural characteristics	
Manufacturing	Share of manufacturing sector	2000
Sector specialization index	GVA in manufacturing (sector C) and financial services (K-N sectors) divided by total industry and Services	2000
R&D	Avg. share of workers in R&D of total workers	2008–2019
Older population	Share of population aged 75 years and above	2000
Population growth	Average population growth	1995–2000
Competition	Business registrations/ deregistrations	2000
	Geographic controls	
Agglomeration	Population density	2000
Regional weights	Weighted neighbors' GVA per working age person	2000
Urban counties	Urban region dummy	2000

informational externalities, geographical locations might influence the club that a region will join. Here, we follow Bartkowska and Riedl (2012) and use each region's neighbor's initial gross value added, equally weighted by the share of total neighbors. Neighbors are defined as counties that share a border with each other, and weights are defined by the total number of bordering counties. An overview of all variables is given in Table 5. Data are retrieved from the regional statistical offices of Germany (Regionalstatistik), capital and price indices are based on their own imputations as described in Section 2.1, and the index of a county being rural or urban is based on the classification by Eurostat, where the category *intermediate* is assigned to being *urban*.[8]

5.2 Ordered logit regression

In order to identify factors that are correlated with membership in a specific convergence club, we follow Bartkowska and Riedl (2012), who propose using an ordered logit model, which is widely applied in the literature for analysing club formation (see, e.g. von Lyncker and Thoennessen (2017), Zhang et al. (2019)). The specification of our model assigns each region to one club c_i, where the ordinal variable c_i takes values of $c_i = 1, \ldots, 5$. Clubs are ordered according to their average output per working age person. Club 1 is, here, the cluster of counties with the highest gross value added, whereas Club 5 represents the club with the least output per working age member among all clubs. The continuous latent variable y_i^* determines the different memberships in each club:

$$y_i^* = X_i\beta + \varepsilon_i \tag{22}$$

where X is the vector of control variables as described in the previous section, vector β includes the regression coefficients, ε_i is assumed to have a logistic distribution with zero mean and a variance of $\pi^2/3$, and y_i^* is the unobserved dependent variable. Using maximum-likelihood techniques, the unknown threshold values and the structural coefficients are jointly estimated.[9] We compute marginal effects of each variable in X for a specific value for c, evaluated at its mean and at the mean of all other controls. Table 6 shows the results of our regression analysis and the cells in each column depict the impact of one unit change in an explanatory variable on the probability that a region will enter the respective club. The numbers in parentheses represent heteroskedasticity-robust standard errors. At the bottom of the table, we further report McFadden's R^2 and the number of counties belonging to each cluster. As our sample of 401 counties consists of one diverging county that can not be attributed to any of the clubs, the number of observations is 400. Furthermore, we conducted a Lipsitz goodness of fit test for ordinal response

[8] Robustness checks with "intermediate" being treated as "rural" are also conducted, with no change in effects. Source: `https://ec.europa.eu/eurostat/web/rural-development/methodology`

[9] For an overview of ordered logit models, see Cameron and Trivedi (2005), chapter 15.

Table 6: Ordered logit regression results

	Club 1	Club 2	Club 3	Club 4	Club 5
Production function indicators					
Output per capita	3×10^{-4} (3×10^{-4})	0.0078* (0.0043)	0.2104*** (0.0583)	0.8785*** (0.2342)	−1.097*** (0.2719)
Participation rate	4×10^{-4} (4×10^{-4})	0.0094* (0.0052)	0.2548** (0.099)	1.0639*** (0.3617)	−1.3285*** (0.4432)
Investment rate	3×10^{-4} (3×10^{-4})	0.006 (0.0039)	0.1621** (0.0764)	0.6767** (0.3104)	−0.845** (0.3797)
Human capital	2×10^{-4} (4×10^{-4})	0.0043 (0.0084)	0.1173 (0.2229)	0.4898 (0.9229)	−0.6116 (1.1525)
Structural characteristics					
Manufacturing	2×10^{-4} (3×10^{-4})	0.0057 (0.0043)	0.1554* (0.0942)	0.6491* (0.3806)	−0.8106* (0.4709)
Specialization	4×10^{-4} (4×10^{-4})	0.0092 (0.0057)	0.2489** (0.1123)	1.0393** (0.4375)	−1.2978** (0.5373)
R&D	0.0000 (0.0000)	0.0000 (0.0000)	5×10^{-4}* (3×10^{-4})	0.002* (0.0012)	−0.0025* (0.0014)
Population growth	0.0000 (0.0000)	-4×10^{-4} (5×10^{-4})	−0.0107 (0.0113)	−0.0447 (0.0473)	0.0559 (0.0588)
Older population	0.0000 (0.0000)	-1×10^{-4}* (0)	−0.0019*** (7×10^{-4})	−0.008*** (0.0028)	0.01*** (0.0033)
Competition	0 (1×10^{-4})	-1×10^{-4} (0.0021)	−0.003 (0.0577)	−0.0126 (0.2411)	0.0157 (0.301)
Geographic controls					
Population density	0.0000 (0.0000)	0.0000 (0.0000)	0.0000 (0.0000)	-1×10^{-4} (1×10^{-4})	1×10^{-4} (1×10^{-4})
Weighted neighbors	0.0000 (0.0000)	-1×10^{-4} (1×10^{-4})	−0.0021* (0.0011)	−0.0086* (0.0044)	0.0107** (0.0054)
Urban	0.0000 (0.0000)	-9×10^{-4} (6×10^{-4})	−0.0239* (0.014)	−0.0997* (0.0578)	0.1245* (0.0712)

McFadden's R^2: 0.37. White heteroskedasticity-robust standard errors in parentheses.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$.

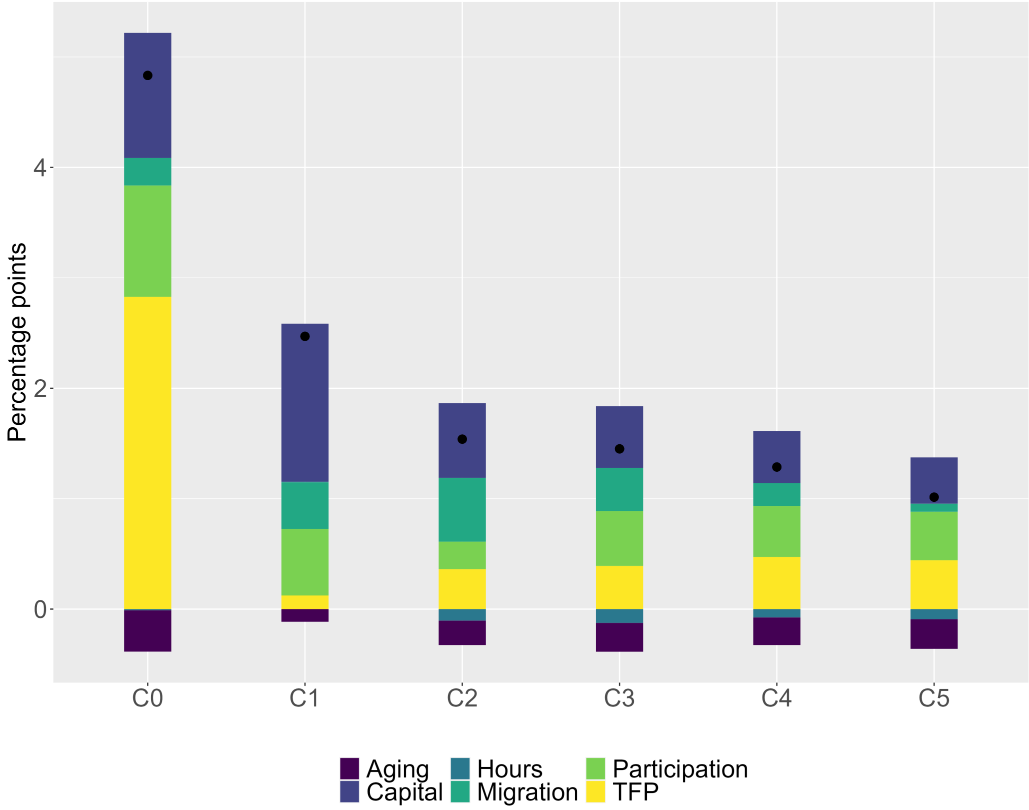
models, which suggested that our fitted model satisfies the proportional odds assumption, giving confidence in the model specification.

With respect to the initial conditions that can be assigned to variables of the production function, we see that the initial per capita output, as well as the participation rate and the investment rate, are associated negatively with the probability of belonging to Club 5, which is the club with the lowest per capita output value. Similarly, an increase in both factors positively affects the probability of belonging to one of the higher-output Clubs 4–2. The less pronounced effects in the upper-output clubs can be due to the fact that the sample size is much smaller for these clubs. While the signs of human capital variable are as expected, we do not see any significant changes in predicted probabilities here. An increase in the share of the manufacturing sector decreases the probability of belonging to the least developed cluster, while we see positive significant increases in the chance of belonging to higher output clubs. This emphasizes the significance of the manufacturing sector for the German economy. Also, we see that an increase in the share of more specialized industries has a strong positive influence on the probability of belonging to a more highly developed club. A similar picture arises for our R&D proxy, which is speaking to the fact that for our sample period, innovative capacities and regional sectoral specialization have affected development of counties positively. On the other hand, we detect a positive significant effect of the share of persons aged above 75 years on the probability of belonging to Club 5, while probabilities turn significantly negative when looking at Clubs 4–2. Demographic change is thus a factor, that can be identified as critical for challenges of regional economic development in Germany. As for the effects of the employed geographic controls, increasing the weighted level of per capita output of neighboring counties seems to have a positive influence on belonging to Club 5, speaking against the theory that high-output counties cluster together. Indeed, looking at figure 9, it seems more that a few high-achievers are surrounded mostly by regions belonging to Club 5. Of course, this relates to the fact that Club 5 dominates our sample, but there do not seem to exist any positive influences from agglomeration of economic activity across counties. Lastly, our results indicate that the marginal probability of belonging to the last convergence club increases if a county is urban. Having a closer look at the distribution of urban versus rural counties indicates that the ratio of urban to rural counties in the last club is higher than that of Club Four. Even though half of all rural counties in the sample belong to Club 5, versus only 35 percent of rural counties belonging to Club 4, the ratio of urban to rural counties is higher in Club 5, through the numerical dominance of both urban counties in the sample and counties in Club 5. However, the estimated coefficient of the variable is significant at a level of only ten percent.

5.3 Differences in growth contributors across convergence clubs

We now analyze how differentials in growth dynamics are composed. For this, we refer to a growth accounting analysis, for which the growth performance of each club is decomposed into the different contributions of its input factors labor, capital, and TFP. As before, TFP is given as Solow residual and represents, therefore, the residual part to

Figure 10: Average growth contributions across clubs, 2002–2019



Note: Period starts from 2002, when net migration data becomes available.
Club 0 is the divergent unit in the sample and represents the city of Wolfsburg.
Club 1: Automotive Powerhouse and Bavarian Silicon Valley: Economic Dominance of Ingolstadt and Munich (County)
Club 2: Urban Economic Giants
Club 3: Innovation and Industry Synergy
Club 4: Cultural Heritage in Southern Germany meets former mining areas in West Germany
Club 5: Rural areas, periphery and East German counties

growth which cannot be attributed to contributions of capital or labor. Similarly to section 3.2, we decompose contributions of the factor labor into growth of the participation rate, the average hours worked, and the working age population, in order to account for growth effects of net migration between counties (see equations 9 and 10). The results are given in figure 10, where the average annual growth of the real gross value added in each club is indicated by black dots, while the contributions of the individual input factors are represented by differently colored segments of the respective bar. Additionally, Figures D.1 and D.2 in the Appendix show in a sample split for the first and second decade of our analysis variations in growth contributions across different years.

The average output growth of Club 1 is characterized by a relatively high contribution of the factors capital and labor. The capital contribution to growth in Club 1 is more than twice as much as in Club 2. Similarly, Club 1 has an average labor contribution of 0.91 percentage points, whereas Club 2 follows with a mean labor growth contribution of 0.50 percentage points. Looking at Club 5, the significant decline in especially the average contribution of labor relative to all other clubs becomes obvious with a value of 0.15 percentage points. Interestingly, differences in labor contribution are mainly due to differences in net migration. Except for those in Club 1, all other counties have negative contributions of the average hours worked, all counties have negative contributions of the natural development of the working age population due to an aging population, and relatively stable contributions of the participation rate. As the contribution of net migration in the last club is almost zero, the contribution of labor is especially low for the club containing half of the counties in our sample. The negative contributions of differences between entries and exits across clusters indicate how demographic change has already challenged output growth in Germany during the last two decades.

Lastly, the divergent county, namely the city of Wolfsburg, is depicted in order to show the striking difference in growth contributions by just one county compared to all other units. Although the TFP of the other clubs ranges between 0.1 and 0.5 percentage points, Wolfsburg, as the location of the major headquarters of car manufacturer Volkswagen, has benefited from a growth in TFP like no other county has. The significant contribution of productivity of around 2.8 percentage points is pushing mean output growth between the years 2000 and 2019 to a value of about five percent. Therefore, Wolfsburg's divergence is plausible.

6 Conclusions

Our study contributes to the understanding of economic inequality among sub-national regions in advanced countries by examining the economic convergence of German counties from 2000 to 2019. Understanding regional convergence processes has important implications for policy makers. If regions are converging to the same level of economic activity in the long run, or if they cluster into distinct development groups, has consequences for the effectiveness of regional policies. A lot of regional funds designed to promote cohesion are aimed at the county level, as, for example, the "Gemeinschaftsaufgabe Verbesserung der regionalen Struktur" (GRW) subsidy program in Germany. However, policy makers risk disappointing the inhabitants of structurally weaker regions if they promise a catch-up process which actually does not take place because the underlying assumption of economic convergence over time does not hold. In such a situation, it might be beneficial to implement transfers to improve living conditions instead of funds for promoting economic activity.

We find limited or no evidence of conditional convergence among these counties. Instead, we identify five distinct clusters of counties, each converging towards their own steady-state growth path, with one outlier experiencing divergence. Using an ordered logit model, we distinguish between factors belonging to the production function, structural characteristics, and geographic controls to assess which of these factors influences the probabilities of belonging to each club. In summary, high initial per capita output, participation rate, and investment rate increase the probability of belonging to the highest-developed club. We derive similar results for our proxies of structural conditions, that resemble R&D and more specialized industries, indicating that innovative activities and sectoral specialization have positively influenced the development of counties. However, demographic change has challenged regional catch-up processes in Germany. We do not find that high-performing counties form spatial clusters. In evaluating not only one of the different hypotheses of convergence, but explicitly testing the conditional as well as the club convergence theory with three inherently different approaches, we are able to assign the form of convergence that we detect to the club convergence hypothesis. Further, we see that a large fraction of counties in East Germany belong to the last club, providing insights into the catch-up process of counties in former GDR territory. Rural and East German counties (Club 5) are by far the largest cluster containing almost half of the sample, whereas the two most highly developed clubs contain only 13 counties. Hence, instead of supporting the existence of overall convergence, our results indicate the evolution of persistent regional disparities within Germany.

7 Declarations

7.1 Funding statement

This research did not receive any funding.

7.2 Author's contribution

AS, CS, and OH jointly developed the research question and overall study design. AS, CS and OH jointly constructed the theoretical framework and derived the main analytical results. AS implemented the empirical strategy, assembled the dataset, and conducted the econometric analysis. CS contributed to the refinement of the empirical strategy. OH supervised the project, contributed to the interpretation of the results, and ensured consistency between theory and empirics. All authors contributed to revisions of the manuscript and approved the final version for submission.

References

Adler, W., Luh, T. and Schwarz, N.: 2022, Entwicklung von Arbeitseinkommen und Lohnquote – Berechnungskonzepte und Ursachen von veränderungen, *WISTA – Wirtschaft und Statistik* **2**.

Aghion, P. and Howitt, P.: 1992, A model of growth through creative destruction, *Econometrica* **60**(2), 323–351.

Arellano, M. and Bond, S.: 1991, Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, *Review of Economic Studies* **58**(2), 277–297.

Arellano, M. and Bover, O.: 1995, Another look at the instrumental variable estimation of error-components models, *Journal of Econometrics* **68**(1), 29–51.

Arif, I.: 2022, Regional club convergence: Evidence from U.S. metropolitan-level data, *Applied Economics* **54**(43), 4979–4990.

Barro, R. J.: 1991, Economic growth in a cross section of countries, *The Quarterly Journal of Economics* **106**(2), 407–443.

Barro, R. J. and Sala-i-Martin, X.: 1995, *Economic Growth*, McGraw-Hill.

Barro, R. J. and Sala-i-Martin, X.: 2004, *Economic Growth*, The MIT Press.

Bartkowska, M. and Riedl, A.: 2012, Regional convergence clubs in Europe: Identification and conditioning factors, *Economic Modelling* **29**(1), 22–31.

Baumol, W. J.: 1986, Productivity growth, convergence, and welfare: What the long-run data show, *American Economic Review* **76**(5), 1072–1085.

Blundell, R. and Bond, S.: 1998, Initial conditions and moment restrictions in dynamic panel data models, *Journal of Econometrics* **87**(1), 115–143.

Cameron, A. and Trivedi, P.: 2005, *Microeconometrics: Methods and Applications*, Cambridge University Press.

Caselli, F., Esquivel, G. and Lefort, F.: 1996, Reopening the convergence debate: A new look at cross-country growth empirics, *Journal of Economic Growth* **1**(3), 363–389.

Chatterji, M. and Dewhurst, J. H. L.: 1996, Convergence clubs and relative economic performance in great britain: 1977–1991, *Regional Studies* **30**(1), 31–39.

Diemer, A., Iammarino, S., Rodríguez-Pose, A. and Storper, M.: 2022, The regional development trap in europe, *Economic Geography* **98**(5), 487–509.

Durlauf, S. and Johnson, P.: 1995, Multiple regimes and cross-country growth behaviour, *Journal of Applied Econometrics* **10**(4), 365–384.

European Commission: 2024, ARDECO database: Annual regional database of the European Commission. Accessed: 2024-11-22.
URL: *https://knowledge4policy.ec.europa.eu/territorial/ardeco-database_en*

Galor, O.: 1996, Convergence? Inferences from theoretical models, *Economic Journal* **106**(437), 1056–1069.

Gennaioli, N., Porta, R. L., de Silanes, F. L. and Shleifer, A.: 2013, Human capital and regional development, *The Quarterly Journal of Economics* **128**(1), 105–164.

Hodrick, R. and Prescott, E.: 1997, Postwar U.S. business cycles: An empirical investigation, *Journal of Money, Credit and Banking* **29**(1), 1–16.

Holtz-Eakin, D., Newey, W. and Rosen, H.: 1988, Estimating vector autoregressions with panel data, *Econometrica* **56**(6), 1371–1395.

Iammarino, S., Rodríguez-Pose, A. and Storper, M.: 2019, Regional inequality in europe: Evidence, theory and policy implications, *Journal of Economic Geography* **19**, 273–298.

Jones, C. I. and Klenow, P. J.: 2016, Beyond GDP? Welfare across countries and time, *American Economic Review* **106**(9), 2426–2457.

Krugman, P. and Venables, A.: 1996, Integration, specialization, and adjustment, *European Economic Review* **40**(3–5), 959–967.

Lin, P.-T. and Robberts, A.: 2024, Regional house price convergence: implications of monetary policy, *Regional Studies* **58**(5), 968–980.
URL: *https://doi.org/10.1080/00343404.2023.2233559*

Lucas, R. J.: 1988, On the mechanics of economic development, *Journal of Monetary Economics* **22**(1), 3–42.

Mankiw, N. G., Romer, D. and Weil, D. N.: 1992, A contribution to the empirics of economic growth, *The Quarterly Journal of Economics* **107**(2), 407–437.

Manzi, G., Alsayed, A., Martins, H. and Saibene, G.: 2023, Regional economic convergence in federation contexts: a comparative analysis of Brazil and the European Union, *Regional Studies* **57**(11), 2269–2284.
URL: *https://doi.org/10.1080/00343404.2023.2167971*

Mora, T.: 2008, Factors conditioning the formation of European regional convergence clubs, *The Annals of Regional Science* **42**(4), 911–927.

Moral-Benito, E.: 2010, Panel growth regressions with general predetermined variables: Likelihood-based estimation and Bayesian averaging, *Working Papers 1006*, CEMFI.

Phillips, P. and Sul, D.: 2007, Transition modeling and econometric convergence tests, *Econometrica* **75**(6), 1771–1855.

Phillips, P. and Sul, D.: 2009, Economic transition and growth, *Journal of Applied Econometrics* **24**(7), 1153–1185.

Quah, D.: 1994, Convergence empirics across economies with (some) capital mobility, *Journal of Economic Growth* **1**, 95–124.

Quah, D. T.: 1996, Empirics for economic growth and convergence, *European Economic Review* **40**(6), 1353–1375.

Ravn, M. and Uhlig, H.: 2002, On adjusting the Hodrick–Prescott filter for the frequency of observations, *The Review of Economics and Statistics* **84**(2), 371–375.

Solow, R. M.: 1956, A contribution to the theory of economic growth, *The Quarterly Journal of Economics* **70**(1), 65–94.

Solow, R. M.: 1957, Technical change and the aggregate production function, *The Review of Economics and Statistics* **39**(3), 312–320.
URL: *http://www.jstor.org/stable/1926047*

Statistische Ämter des Bundes und der Länder: 2024a, Regionaldatenbank Deutschland. Accessed: 2024-11-22.
URL: *https://www.regionalstatistik.de*

Statistische Ämter des Bundes und der Länder: 2024b, Volkswirtschaftliche Gesamtrechnungen der Länder (VGR der Länder). Accessed: 2024-11-22.
URL: *https://www.statistikportal.de/de/vgrdl*

von Lyncker, K. and Thoennessen, R.: 2017, Regional club convergence in the EU: evidence from a panel data analysis, *Empirical Economics* **52**(2), 525–553.

Young, A., Higgins, M. and Levy, D.: 2008, Sigma convergence versus beta convergence: Evidence from U.S. county-level data, *Journal of Money, Credit and Banking* **40**(5), 1083–1093.

Zhang, W., Xu, W. and Wang, X.: 2019, Regional convergence clubs in China: identification and conditioning factors, *The Annals of Regional Science* **62**.

A Data

In this section, we investigate the robustness of the capital stock and the price index, and describe the adjustments that we applied to our data. Figure A.1 exploits the fact that statistical offices report values for the capital stock on the state level and compares those values with the ones that we would get in assuming constant capital intensities on national level. We weight these capital intensities by state-level sectoral labor shares and find that the percentage deviation of the estimated capital stock from the actual is maximally two percent (see Figure A.2), indicating robustness of the employed estimation method.

Figure A.1: State-level capital estimated with national capital intensities (log-log)

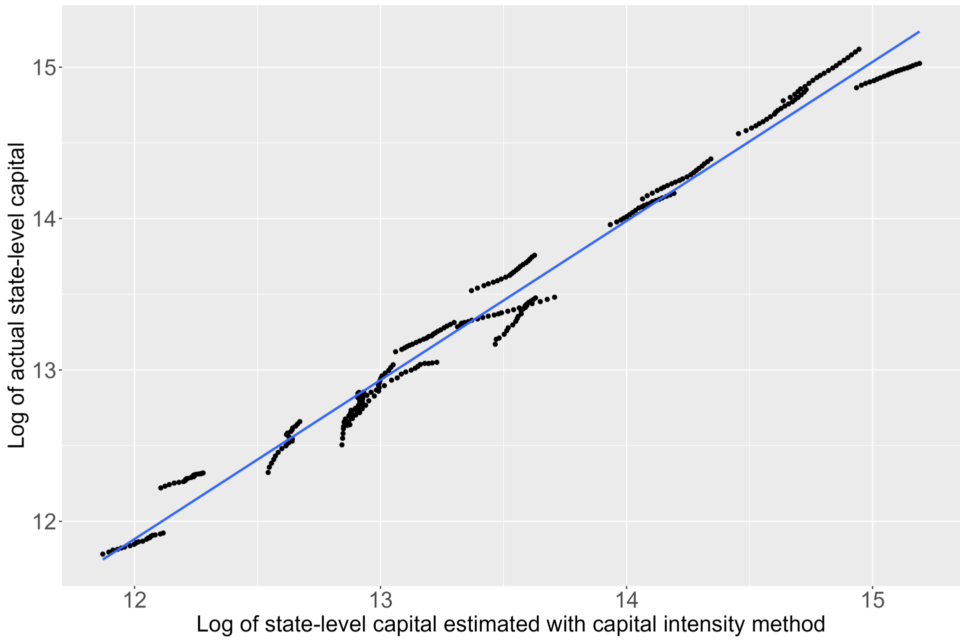
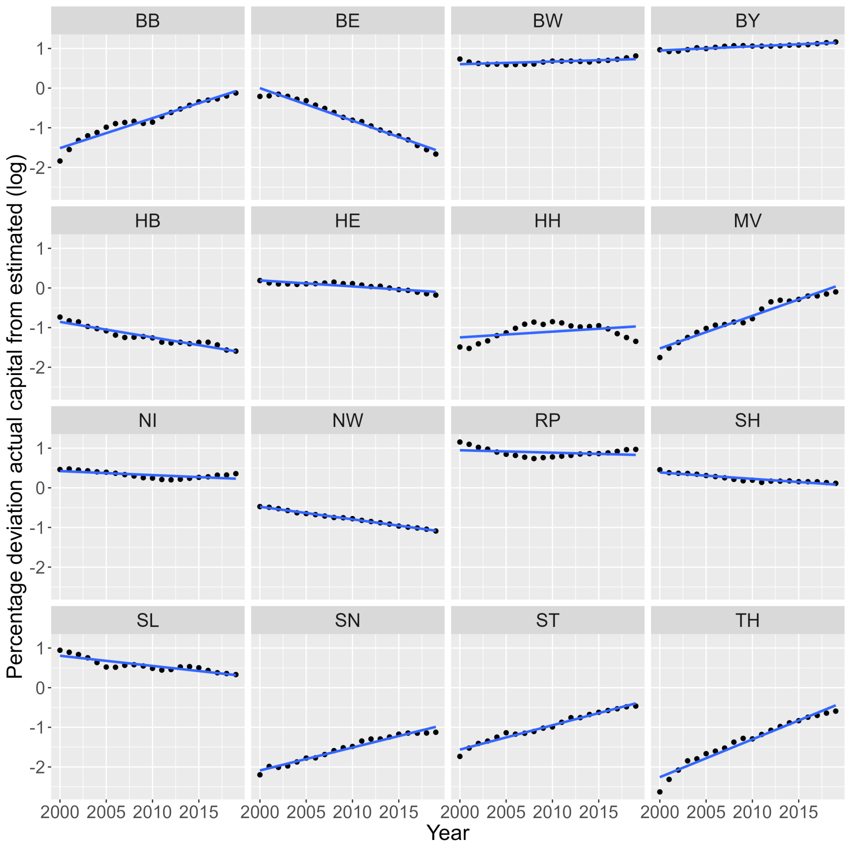


Figure A.3 shows the percentage deviation of real state-level GVA to aggregated county-level real GVA, which has been deflated by regional price indices as described in Section 2.1. It aims to give insights on how our regional price indices vary with respect to the state-level price indices, as the percentage deviation can be traced back to differences in the regional, estimated indices to the state-level indices. The differences range between zero and 0.8 percent.

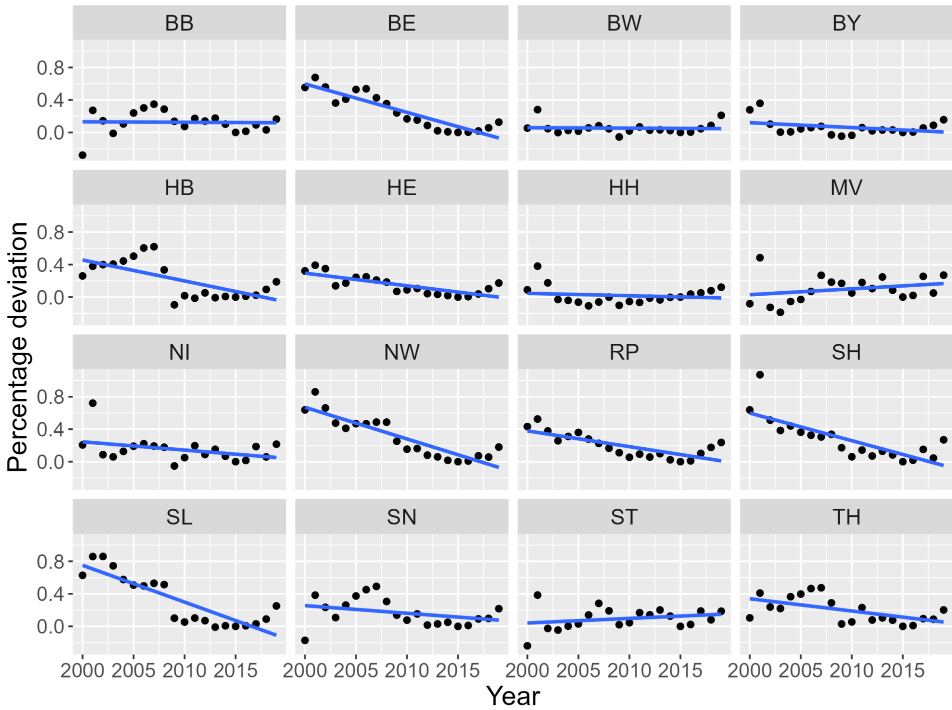
TFP is given as the Solow residual. Therefore, we need to specify the labor share, that is, the ratio of labor compensation to GVA. Because labor compensation does not include income from self-employed persons, we adjust labor compensation by the ratio of employed persons to employees, assuming that the average wage of self-employed persons is equal to the average wage of employed persons. This is in accordance with the modeling approach of the German Federal Statistical Office (Adler et al., 2022).

Figure A.2: Percentage deviation of actual capital from estimated (log-log)



Lastly, 33 of the 401 German counties have changed their borders between 2000 and 2019. The data reported by the Federal Statistical Office are not mapped back according to the current county borders. We therefore adjust the data for those counties accordingly, and for cases where counties were not merged with a full county but only with a fraction of a county, we apply population weights.

Figure A.3: Percentage deviation of state level GVA (real) from aggregated county-level GVA (real)



B Club membership by county

Table B.1: Identified clubs and counties

Code	County	Code	County
	Club 0		
DE913	Wolfsburg, Kreisfreie Stadt		
	Club 1		
DE211	Ingolstadt, Kreisfreie Stadt	DE21H	München, Landkreis
	Club 2		
DE111	Stuttgart, Landeshauptstadt, Stadtkreis	DE232	Regensburg, Kreisfreie Stadt
DE112	Böblingen, Landkreis	DE243	Coburg, Kreisfreie Stadt
DE118	Heilbronn, Landkreis	DE252	Erlangen, Kreisfreie Stadt
DE212	München, Landeshauptstadt, Kreisfreie Stadt	DE262	Schweinfurt, Kreisfreie Stadt
DE712	Frankfurt am Main, Kreisfreie Stadt	DE942	Emden, Kreisfreie Stadt
DEB34	Ludwigshafen am Rhein, Kreisfreie Stadt		
	Club 3		
DE115	Ludwigsburg, Landkreis	DE213	Rosenheim, Kreisfreie Stadt
DE117	Heilbronn, Stadtkreis	DE21M	Traunstein, Landkreis
DE119	Hohenlohekreis	DE221	Landshut, Kreisfreie Stadt
DE11D	Ostalbkreis	DE222	Passau, Kreisfreie Stadt
DE121	Baden-Baden, Stadtkreis	DE22C	Dingolfing-Landau, Landkreis
DE122	Karlsruhe, Stadtkreis	DE231	Amberg, Kreisfreie Stadt
DE126	Mannheim, Universitätsstadt, Stadtkreis	DE23A	Tirschenreuth, Landkreis
DE131	Freiburg im Breisgau, Stadtkreis	DE241	Bamberg, Kreisfreie Stadt
DE135	Rottweil, Landkreis	DE242	Bayreuth, Kreisfreie Stadt
DE137	Tuttlingen, Landkreis	DE249	Hof, Landkreis
DE144	Ulm, Universitätsstadt, Stadtkreis	DE251	Ansbach, Kreisfreie Stadt
DE146	Biberach, Landkreis	DE254	Nürnberg, Kreisfreie Stadt
DE147	Bodenseekreis	DE257	Erlangen-Höchstadt, Landkreis

Continued on next page

Continued from previous page

Code	County	Code	County
DE148	Ravensburg, Landkreis	DE261	Aschaffenburg, Kreisfreie Stadt
DE263	Würzburg, Kreisfreie Stadt	DE266	Rhön-Grabfeld, Landkreis
DE274	Memmingen, Kreisfreie Stadt	DE27A	Lindau (Bodensee), Landkreis
DE27D	Donau-Ries, Landkreis	DE300	Berlin
DE40H	Teltow-Fläming, Landkreis	DE600	Hamburg
DE711	Darmstadt, Wissenschaftsstadt, Kreisfreie Stadt	DE714	Wiesbaden, Landeshauptstadt, Kreisfreie Stadt
DE71A	Main-Taunus-Kreis	DE803	Rostock, Hansestadt, Kreisfreie Stadt
DE911	Braunschweig, Kreisfreie Stadt	DE912	Salzgitter, Kreisfreie Stadt
DEA11	Düsseldorf, Kreisfreie Stadt	DEA22	Bonn, Kreisfreie Stadt
DEA23	Köln, Kreisfreie Stadt	DEA42	Gütersloh, Kreis
DEB11	Koblenz, Kreisfreie Stadt	DEB38	Speyer, Kreisfreie Stadt
DEF04	Neumünster, Kreisfreie Stadt	DEG03	Jena, Kreisfreie Stadt
DEG0N	Eisenach, Kreisfreie Stadt		
	Club 4		
DE113	Esslingen, Landkreis	DE214	Altötting, Landkreis
DE116	Rems-Murr-Kreis	DE215	Berchtesgadener Land, Landkreis
DE11A	Schwäbisch Hall, Landkreis	DE219	Eichstätt, Landkreis
DE11B	Main-Tauber-Kreis	DE21B	Freising, Landkreis
DE123	Karlsruhe, Landkreis	DE21E	Landsberg am Lech, Landkreis
DE124	Rastatt, Landkreis	DE21F	Miesbach, Landkreis
DE125	Heidelberg, Stadtkreis	DE21G	Mühldorf a.Inn, Landkreis
DE128	Rhein-Neckar-Kreis	DE21J	Pfaffenhofen a.d.Ilm, Landkreis
DE129	Pforzheim, Stadtkreis	DE21K	Rosenheim, Landkreis
DE12C	Freudenstadt, Landkreis	DE21L	Starnberg, Landkreis
DE133	Emmendingen, Landkreis	DE21N	Weilheim-Schongau, Landkreis
DE134	Ortenaukreis	DE223	Straubing, Kreisfreie Stadt
DE136	Schwarzwald-Baar-Kreis	DE224	Deggendorf, Landkreis
DE138	Konstanz, Landkreis	DE225	Freyung-Grafenau, Landkreis
DE141	Reutlingen, Landkreis	DE227	Landshut, Landkreis
DE142	Tübingen, Landkreis	DE229	Regen, Landkreis
DE143	Zollernalbkreis	DE233	Weiden i.d.OPf., Kreisfreie Stadt

Continued on next page

Continued from previous page

Code	County	Code	County
DE149	Sigmaringen, Landkreis	DE235	Cham, Landkreis
DE236	Neumarkt i.d.OPf., Landkreis	DE237	Neustadt a.d.Waldnaab, Landkreis
DE239	Schwandorf, Landkreis	DE244	Hof, Kreisfreie Stadt
DE248	Forchheim, Landkreis	DE24B	Kulmbach, Landkreis
DE24D	Wunsiedel i.Fichtelgebirge, Landkreis	DE267	Haßberge, Landkreis
DE268	Kitzingen, Landkreis	DE269	Miltenberg, Landkreis
DE26A	Main-Spessart, Landkreis	DE271	Augsburg, Kreisfreie Stadt
DE273	Kempten (Allgäu), Kreisfreie Stadt	DE277	Dillingen a.d.Donau, Landkreis
DE278	Günzburg, Landkreis	DE279	Neu-Ulm, Landkreis
DE27B	Ostallgäu, Landkreis	DE27C	Unterallgäu, Landkreis
DE27E	Oberallgäu, Landkreis	DE401	Brandenburg an der Havel, Kreisfreie Stadt
DE402	Cottbus, Kreisfreie Stadt	DE404	Potsdam, Kreisfreie Stadt
DE40B	Oberspreewald-Lausitz, Landkreis	DE40F	Prignitz, Landkreis
DE40G	Spree-Neiße, Landkreis	DE40I	Uckermark, Landkreis
DE501	Bremen, Kreisfreie Stadt	DE717	Groß-Gerau, Landkreis
DE718	Hochtaunuskreis	DE719	Main-Kinzig-Kreis
DE71C	Offenbach, Landkreis	DE724	Marburg-Biedenkopf, Landkreis
DE731	Kassel, documenta-Stadt, Kreisfreie Stadt	DE732	Fulda, Landkreis
DE734	Kassel, Landkreis	DE736	Waldeck-Frankenberg, Landkreis
DE804	Schwerin, Landeshauptstadt, Kreisfreie Stadt	DE91C	Göttingen, Landkreis
DE923	Hameln-Pyrmont, Landkreis	DE927	Nienburg (Weser), Landkreis
DE929	Region Hannover, Landkreis	DE937	Rotenburg (Wümme), Landkreis
DE938	Heidekreis, Landkreis	DE943	Oldenburg (Oldenburg), Kreisfreie Stadt
DE944	Osnabrück, Kreisfreie Stadt	DE945	Wilhelmshaven, Kreisfreie Stadt
DE946	Ammerland, Landkreis	DE948	Cloppenburg, Landkreis
DE949	Emsland, Landkreis	DE94F	Vechta, Landkreis

Continued on next page

Continued from previous page

Code	County	Code	County
DEA13	Essen, Kreisfreie Stadt	DEA14	Krefeld, Kreisfreie Stadt
DEA18	Remscheid, Kreisfreie Stadt	DEA1A	Wuppertal, Kreisfreie Stadt
DEA1C	Mettmann, Kreis	DEA1D	Rhein-Kreis Neuss, Kreis
DEB1B	Westerwaldkreis	DEB1D	Rhein-Hunsrück-Kreis
DEB24	Vulkaneifel, Landkreis	DEB32	Kaiserslautern, Kreisfreie Stadt
DEB33	Landau in der Pfalz, Kreisfreie Stadt	DEB35	Mainz, Kreisfreie Stadt
DEB37	Pirmasens, Kreisfreie Stadt	DEB39	Worms, Kreisfreie Stadt
DEC01	Saarbrücken, Regionalverband	DEC05	Saarpfalz-Kreis
DED21	Dresden, Kreisfreie Stadt	DED41	Chemnitz, Kreisfreie Stadt
DED45	Zwickau, Landkreis	DED51	Leipzig, Kreisfreie Stadt
DEG01	Erfurt, Kreisfreie Stadt	DEG02	Gera, Kreisfreie Stadt
	Club 5		
DE114	Göppingen, Landkreis	DE216	Bad Tölz-Wolfratshausen, Landkreis
DE11C	Heidenheim, Landkreis	DE217	Dachau, Landkreis
DE127	Neckar-Odenwald-Kreis	DE218	Ebersberg, Landkreis
DE12A	Calw, Landkreis	DE21A	Erding, Landkreis
DE12B	Enzkreis	DE21C	Fürstenfeldbruck, Landkreis
DE132	Breisgau-Hochschwarzwald, Landkreis	DE21D	Garmisch-Partenkirchen, Landkreis
DE139	Lörrach, Landkreis	DE21I	Neuburg-Schrobenhausen, Landkreis
DE13A	Waldshut, Landkreis	DE226	Kelheim, Landkreis
DE145	Alb-Donau-Kreis	DE228	Passau, Landkreis
DE22A	Rottal-Inn, Landkreis	DE22B	Straubing-Bogen, Landkreis
DE234	Amberg-Sulzbach, Landkreis	DE238	Regensburg, Landkreis
DE245	Bamberg, Landkreis	DE246	Bayreuth, Landkreis
DE247	Coburg, Landkreis	DE24A	Kronach, Landkreis
DE24C	Lichtenfels, Landkreis	DE253	Fürth, Kreisfreie Stadt
DE255	Schwabach, Kreisfreie Stadt	DE256	Ansbach, Landkreis
DE258	Fürth, Landkreis	DE259	Nürnberger Land, Landkreis
DE25A	Neustadt a.d.Aisch-Bad Windsheim, Landkreis	DE25B	Roth, Landkreis

Continued on next page

Continued from previous page

Code	County	Code	County
DE25C	Weißenburg-Gunzenhausen, Landkreis	DE264	Aschaffenburg, Landkreis
DE265	Bad Kissingen, Landkreis	DE26B	Schweinfurt, Landkreis
DE26C	Würzburg, Landkreis	DE272	Kaufbeuren, Kreisfreie Stadt
DE275	Aichach-Friedberg, Landkreis	DE276	Augsburg, Landkreis
DE403	Frankfurt (Oder), Kreisfreie Stadt	DE405	Barnim, Landkreis
DE406	Dahme-Spreewald, Landkreis	DE407	Elbe-Elster, Landkreis
DE408	Havelland, Landkreis	DE409	Märkisch-Oderland, Landkreis
DE40A	Oberhavel, Landkreis	DE40C	Oder-Spree, Landkreis
DE40D	Ostprignitz-Ruppin, Landkreis	DE40E	Potsdam-Mittelmark, Landkreis
DE502	Bremerhaven, Kreisfreie Stadt	DE713	Offenbach am Main, Kreisfreie Stadt
DE715	Bergstraße, Landkreis	DE716	Darmstadt-Dieburg, Landkreis
DE71B	Odenwaldkreis	DE71D	Rheingau-Taunus-Kreis
DE71E	Wetteraukreis	DE721	Gießen, Landkreis
DE722	Lahn-Dill-Kreis	DE723	Limburg-Weilburg, Landkreis
DE725	Vogelsbergkreis	DE733	Hersfeld-Rotenburg, Landkreis
DE735	Schwalm-Eder-Kreis	DE737	Werra-Meißner-Kreis
DE80J	Mecklenburgische Seenplatte, Landkreis	DE80K	Landkreis Rostock
DE80L	Vorpommern-Rügen, Landkreis	DE80M	Nordwestmecklenburg, Landkreis
DE80N	Vorpommern-Greifswald, Landkreis	DE80O	Ludwigslust-Parchim, Landkreis
DE914	Gifhorn, Landkreis	DE916	Goslar, Landkreis
DE917	Helmstedt, Landkreis	DE918	Northeim, Landkreis
DE91A	Peine, Landkreis	DE91B	Wolfenbüttel, Landkreis
DE922	Diepholz, Landkreis	DE925	Hildesheim, Landkreis
DE926	Holzminden, Landkreis	DE928	Schaumburg, Landkreis
DEA12	Duisburg, Kreisfreie Stadt	DEA15	Mönchengladbach, Kreisfreie Stadt
DEA16	Mülheim an der Ruhr, Kreisfreie Stadt	DEA17	Oberhausen, Kreisfreie Stadt

Continued on next page

Continued from previous page

Code	County	Code	County
DEB12	Ahrweiler, Landkreis	DEB13	Altenkirchen (Westerwald), Landkreis
DEB14	Bad Kreuznach, Landkreis	DEB15	Birkenfeld, Landkreis
DEB21	Trier, Kreisfreie Stadt	DEB22	Bernkastel-Wittlich, Landkreis
DEB23	Eifelkreis Bitburg-Prüm	DEB25	Trier-Saarburg, Landkreis
DEC02	Merzig-Wadern, Landkreis	DEC03	Neunkirchen, Landkreis
DED2C	Bautzen, Landkreis	DED2F	Sächsische Schweiz-Osterzgebirge, Landkreis
DED42	Erzgebirgskreis	DED43	Mittelsachsen, Landkreis
DED44	Vogtlandkreis	DED53	Nordsachsen, Landkreis
DEG05	Weimar, Kreisfreie Stadt	DEG07	Nordhausen, Landkreis
DEG09	Unstrut-Hainich-Kreis	DEG0A	Kyffhäuserkreis
DEG0C	Gotha, Landkreis	DEG0D	Sömmerda, Landkreis

Note: The codes are according to the Nomenclature of Territorial Units for Statistics 2021 (NUTS).

C Club membership by labor market region

Figure C.1: Labor-market regions

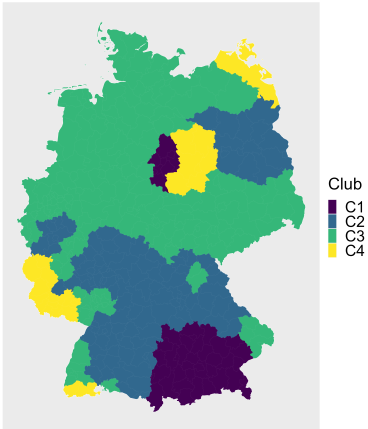


Figure C.2: Counties

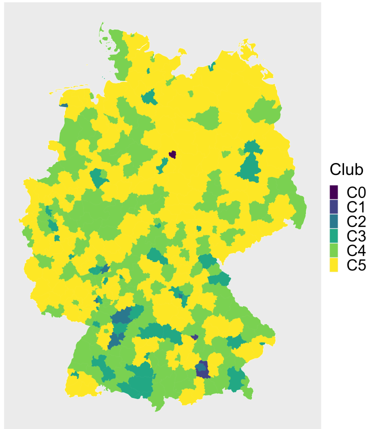


Figure C.3: Transition paths for labor-market clubs

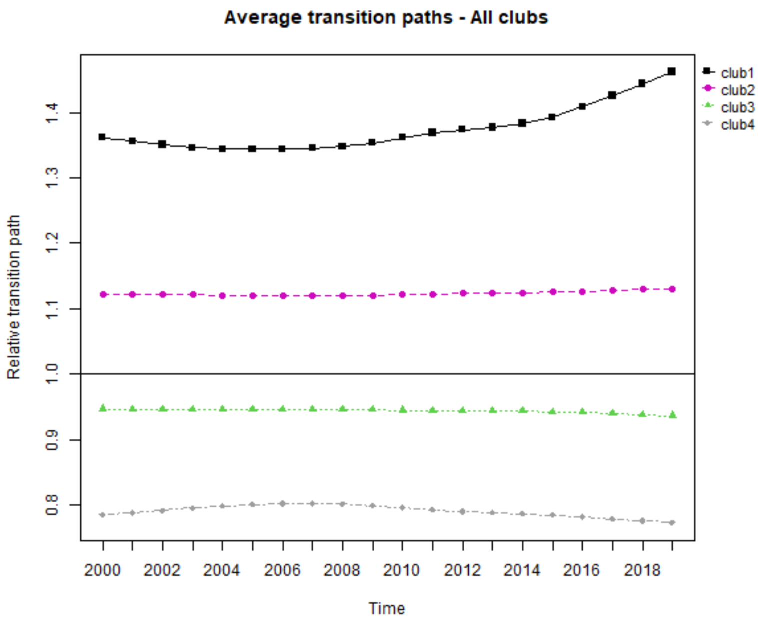


Table C.1: Identified Clubs and Labor-Market Regions

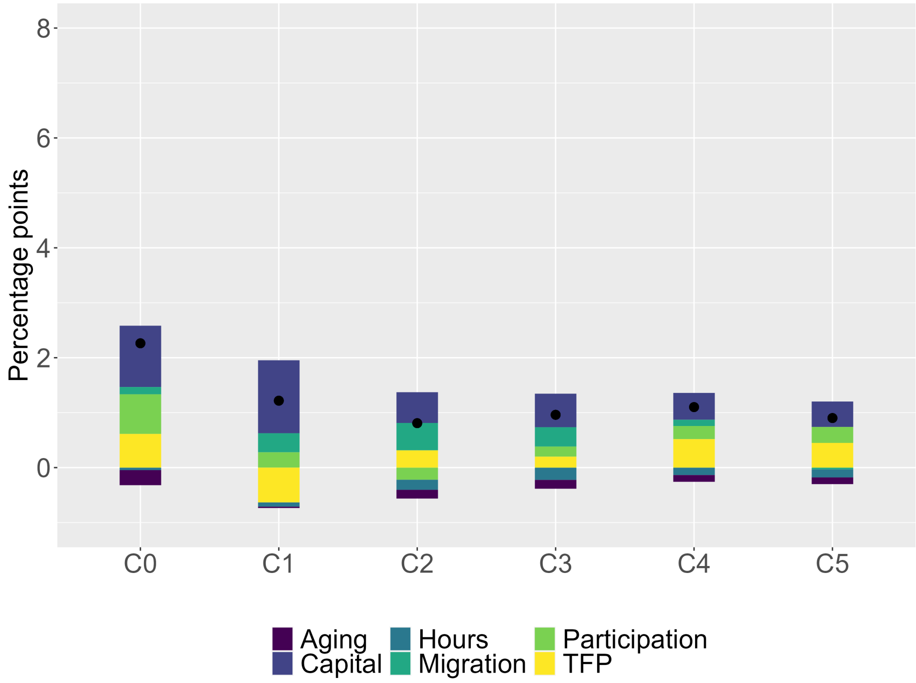
Key	Region	Key	Region
		Club 1	
03101	Braunschweig/Wolfsburg	09162	München
	Not the whole table included for proofreading.		
05315	Köln	06412	Frankfurt a.M.
08111	Stuttgart	08212	Karlsruhe
08326	Villingen-Schwenningen	08421	Ulm
08436	Ravensburg	09362	Regensburg
09363	Weiden i.d.OPf.	09463	Coburg
09464	Hof	09479	Wunsiedel i.F.
09564	Nürnberg	09662	Schweinfurt
09663	Würzburg	11000	Berlin
		Club 3	
02000	Hamburg	03159	Göttingen
03241	Hannover	03403	Oldenburg(O.)
03404	Osnabrück	04011	Bremen
05113	Düsseldorf-Ruhr	05334	Aachen
05515	Münster	05711	Bielefeld/Paderborn
05970	Siegen	06611	Kassel
07111	Koblenz	08222	Mannheim
08311	Freiburg i.Br.	08317	Offenburg
08335	Konstanz	09262	Passau
09462	Bayreuth	13003	Rostock
13071	Mecklenburgische Seenplatte	14511	Chemnitz
14612	Dresden	14713	Leipzig
16051	Erfurt	16054	Suhl
		Club 4	
07211	Trier	08336	Lörrach
10041	Saarbrücken	13075	Greifswald/Stralsund
15003	Magdeburg	15085	Harz

Note: The keys identify 50 labor market regions: https://statistik.arbeitsagentur.de

D Growth contributions – sample split

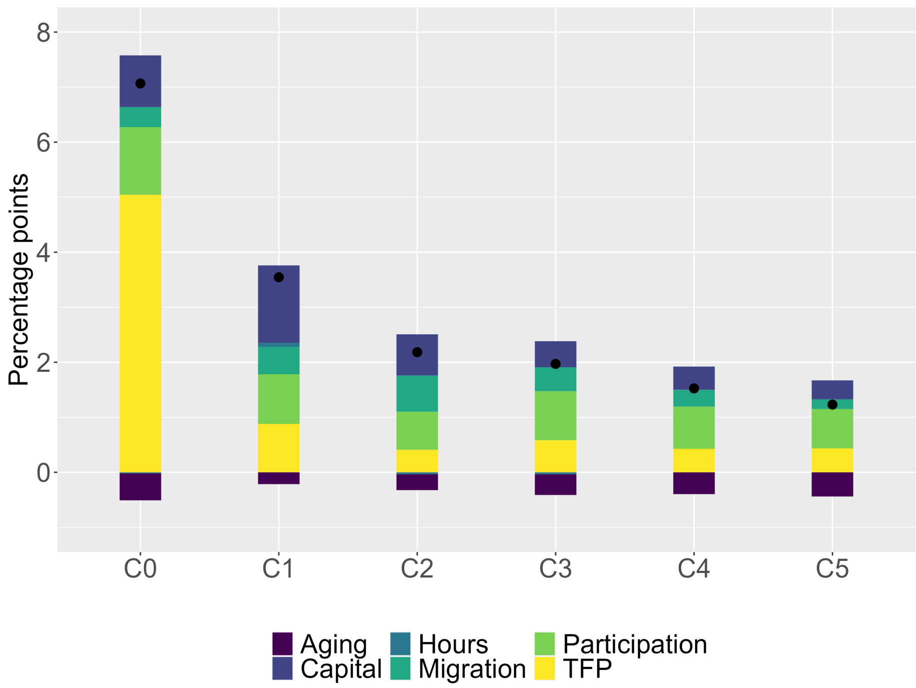
Figures D.1 and D.2 show variations in growth contributions averaged over the first and second decade of our analysis. Evidently, growth of all clusters is higher in the second subperiod; for Club 1 and the diverging county Wolfsburg, average output growth between 2011 and 2019 is even more than double the growth of the first decade. While the negative contribution of total hours worked has vanished to around zero in the second subperiod, the impact of net migration has been stayed constant for the higher developed clusters while, for Club 5, this average contribution is in the 2010's slightly positive. Overall, the positive impact of net migration is neutralized through the negative impact of aging, so that the participation rate is governing the contribution of labor only.

Figure D.1: Average growth contributions across clubs, 2002–2010



Note: Club 0 is the diverging unit in the sample and represents the city of Wolfsburg.

Figure D.2: Average growth contributions across clubs, 2011–2019



Note: Club 0 is the diverging unit in the sample and represents the city of Wolfsburg.

Halle Institute for Economic Research –
Member of the Leibniz Association

Kleine Maerkerstrasse 8
D-06108 Halle (Saale), Germany

Postal Adress: P.O. Box 11 03 61
D-06017 Halle (Saale), Germany

Tel +49 345 7753 60
Fax +49 345 7753 820

www.iwh-halle.de

ISSN 2194-2188

Leibniz Association

The IWH is funded by the federal government and the German federal states.