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Local Effects of Education and Age Groups on Unemployment in Germany

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Abstract

This article provides a comprehensive analysis of how regional changes in the age and education distribution of the labour force affect local and neighbourhood unemployment rates. Based on theoretical considerations, we argue that differences in job search, separation, and commuting are key factors in group differences, and therefore, changes in relative group size affect the level of unemployment. The empirical analysis focuses on local labour markets in Germany, using a dynamic spatial panel data model. According to the estimates, an increasing proportion of young and/or low-educated workers raises local unemployment, while larger proportions of older prime-age and/or highly educated workers raise unemployment in neighbouring labour markets. As a result, the recent ageing and education developments in the German labour force have led to a 25 per cent reduction in the unemployment rate.

Keywords— Regional Unemployment, Spatial Interactions, Aging, Human Capital, Labour Mobility

JEL classification— R23, R12, J11, J24, J61

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1 Introduction

The unemployment rate is often used as an indicator of the overall economic situation. However, it can also be seen as an average unemployment risk that takes into account different groups of people with varying levels of education and age. For instance, those with lower levels of education are more likely to be unemployed than those with higher levels of education.[1] A change in their group shares changes the overall unemployment rate, even if the unemployment rate of both groups does not change. Similarly, younger workers are more likely to be unemployed than older workers.[2] Over the past two decades, the OECD average has shown that unemployment rates decrease with increasing age and education levels, regardless of the size of the groups and economic cycles. This means that changes in the distribution of age and education groups are crucial factors that affect the unemployment rate in the long term.

The aim of this article is to analyse how regional changes in the age and education distribution of the labour force affect local and neighbourhood unemployment rates.[3] Based on theoretical considerations, we argue that differences in job search, separation, and mobility in terms of commuting are key factors in group differences, and therefore, changes in relative group size affect the level of overall unemployment. Both age and education have a compositional impact on unemployment in the local and neighbouring regions. Our hypothesis is that the recent changes in the distribution of education and age in the German labour force account for substantially reducing the unemployment rate.

Our research considerably contributes to the literature by empirically assessing compositional effects on unemployment at the regional level. We consider a spatial econometric approach and data on the local distribution of age and education. An ageing process and an increased education level of the labour force characterise the period under study. Our dynamic space-time panel data model (spatial Durbin model) reveals that a rising share of youth and/or low-educated workers increases local unemployment in Germany. However, these groups do not affect unemployment in the neighbouring labour market. Conversely, a larger share of older prime-age and/or highly educated workers in the surrounding area raises the unemployment rate in the local region. These groups have statistically weak negative effects on unemployment in their home area. In conclusion, the ageing of the labour force and the rising education level reduce overall unemployment. Furthermore, the current changes in age and education groups are almost equally important and account for an unemployment rate reduction of about 25 per cent. These findings have

[1] The OECD average for the lower than upper secondary education group is 10.8% and 4.4% for those with tertiary education in 2021.

[2] The OECD average for the youth is 12.8% and 4.7% for the group of workers 55-64 years in 2021.

[3] We consider only employed and unemployed individuals of the working-age population. In addition, we do not consider other individual characteristics like gender or work experience. For details, see section 4.1.

practical implications for policymakers and labour market analysts in understanding and addressing regional unemployment.

The article is organised as follows: Section 2 offers a literature overview, and Section 3 provides some theoretical considerations. Section 4 describes the data and the econometric approach and reports and discusses the estimated results. Section 5 concludes.

2 Literature Review

During the early 1970s, the youth population increased in many developed countries. Today, we are witnessing a substantial rise in the proportion of older workers, which has implications for the labour market when younger and older workers are imperfect substitutes (Easterlin et al., 1978).[4] While Easterlins' cohort crowding hypothesis primarily focuses on marriage, fertility, wages, and labour market participation, Perry (1970) focused on the relationship between population group size and employment. Based on macroeconomic data, the subsequent scholarly discussion concludes that a larger share of the working-age population youth raises the overall unemployment rate. This is because the youth often have the highest unemployment level among age groups.[5]

In contrast, Shimer (2001) concludes that the labour supply of many young people can reduce the overall unemployment rate using US state-level panel data. He argues that a higher share of young individuals in the working-age population can lead to an increase in job creation due to their higher search intensity. A similar result is found in Nordström Skans (2005), who uses Swedish data and concludes that younger workers can benefit from belonging to a large cohort in terms of reduced unemployment.

Garloff et al. (2013) conducted a study to analyze the impact of smaller labour market entry cohorts on unemployment and the direct effect of the age structure on unemployment in West Germany. They found that if the age distribution of the labour force remained unchanged, the unemployment rate would have been higher. As the size of the younger generation entering the labour market in Germany has been decreasing, the demographic change could enhance job opportunities and reduce the unemployment rate. Ochsen (2021) analyses the local effect of the age distribution of the working-age population on unemployment. Using US county-level data, he applies a dynamic space-time panel data model and considers different age groups in the local and neighbouring regions. The results provide strong evidence that (spatial) age group changes are an important long-term driver of overall unemployment change. Ageing of the working-age population reduces overall unemployment, and the present changing age structure leads to a long-term reduction of the US unemployment rate.

[4] Jimeno and Rodriguez-Palenzuela (2003) find that such imperfections increase with strong employment protection.

[5] See, for example, Biagi and Lucifora (2008) for a summary.

A major benefit of education is that the unemployment risk decreases with an increasing education level (Mincer, 1991). For example, Acemoglu (1998, 2002, 2003) discusses the role of technological change and wages for shifts to more skilled and less unskilled workers. Consequently, the distribution in an economy shifts continuously towards more educated workers, similar to the ageing process. When employers prefer college graduates for jobs that require a high school degree, the relative demand for college graduates rises. Early literature that finds empirical evidence for this are Teulings and Koopmanschap (1989), Howe (1993), and van Ours & Ridder (1995). The evidence that larger groups of better-educated individuals crowd out less-educated individuals also has consequences for the low-educated unemployed, as, for example, Wolbers (2000), Arberg (2003), Gesthuizen & Wolbers (2010), and Abrassart (2015) point out. Therefore, creating low-skilled jobs may not necessarily improve the employability of low-skilled workers.

The literature discussed analyses either the effects of ageing or education on unemployment. An exception is a study by Biagi and Lucifora (2008), who examine the effects of demographic and educational changes on the evolution of unemployment rates for a panel of European countries. Their research findings suggest that demographic and education changes affect young and adult workers and more or less educated individuals differently. The study reveals that changes in the population age structure (baby bust) positively relate to the youth unemployment rate, whereas changes in the educational structure (education boom) reduce unemployment among the more educated.

Finally, national-level data are not appropriate for covering within-country mobility. In small local regions, spatial mobility (in terms of commuting) is related to local labour market tightness. In addition, spatial mobility is different for age groups (the youth is more mobile than older workers) and education groups (the highly educated are more mobile than low-educated workers).[6] The effects of a changing age structure in the local labour force on unemployment in a spatial interaction model are considered only in the study by Ochsen (2021). Concerning educational distribution and spatial mobility, Kulu et al. (2018) report that changes in population composition, mainly increased enrolment in higher education, account for much of the rising spatial mobility using data for Sweden. Using French data, Lemistre and Moreau (2009) find that returns to spatial mobility for men increase with education.

3 Theoretical Considerations

Shifts in the labour force to larger shares of educated and older workers affect the unemployment rate when group-specific unemployment rates differ. To analyse this, we divide the labour force into two groups, group 1 and group 2. Age group 1 represents the

[6] For a more detailed discussion, see, for example, Brücker and Trübswetter (2007) and Hunt (2000).

younger workers (y), and age group 2 represents the older workers (o). For education, we distinguish between low-educated (μ) as group 1 and high-educated (h) as group 2. For simplicity, the labour force consists of these two groups only (either age or education), with a labour force share of p for the first group and $1-p$ for the second group. Workers are either employed or unemployed; if they are unemployed, we assume they are seeking a new job. The aggregated unemployment rate u consists of the group-specific rates weighted at the respective labour force share: $u = pu_1 + (1-p)\,u_2$.

In the standard search and matching framework, equilibrium unemployment is explained by two flow rates: the separation rate s and the job finding rate $f(\theta)$. While s is the risk of job loss and the corresponding flow to unemployment, $f(\theta)$ is the probability of an unemployed person finding new employment (with market tightness θ). Given that u, u_1, and u_2 are in equilibrium, we have:

$$u^* = pu_1^* + (1-p)\,u_2^* = p\frac{s_1}{s_1 + f_1(\theta)} + (1-p)\,\frac{s_2}{s_2 + f_2(\theta)} \tag{1}$$

It is easy to see that a rising p increases (decreases) u^* when $u_1^* > u_2^*$ ($u_1^* < u_2^*$). In addition, for a given distribution of the groups, the unemployment rate rises if at least one group's unemployment rate increases. Finally, the flow rates into and out of unemployment can explain the group-specific unemployment rate change.

To point out that group-specific flows and unemployment rates matter, we use aggregated stock and flow data provided by the German Federal Employment Agency. Table 1 provides average values for the youth (15 to 24 years) and older workers (50 to 64 years) as well as for low (no apprenticeship) and high-educated workers (academic education) for the period 2008 to 2018 using monthly data. u_i^* is calculated according to eq. (1) and u_i is the usual unemployment rate, calculated using the group-specific stock of the unemployed divided by the group-specific stock of the labour force.

Table 1 about here

The separation risk and job-finding rate are above average for youth. Separation is above the average for the low-educated workers, but job finding is below. This difference is the reason for the vast differences between these two groups in terms of the unemployment rate. Older workers and those who are highly educated have separation rates below the average. Concerning job finding, these two groups differ; the highly educated are above the average, and older workers are below. Again, this difference explains the difference in unemployment rates.

Another important finding is that the age groups have a clear, dynamic pattern. Compared to older workers, youth is more often unemployed but also faster reemployed. In contrast, highly educated workers benefit from favourable flow rates, while the low-educated suffer from adverse flow rates concerning the unemployment rate. Within all groups, both average unemployment rates in Table 1 are very similar, notwithstanding that the equilibrium unemployment rate is a simplified concept. Hence, the flow rates are useful in explaining what happens if the share of age or education groups changes. For example, from an aggregated perspective, we can argue that less low-educated and more high-educated workers mean less separation and faster job finding, which decreases the unemployment rate. However, more older and less younger workers result in less separation but also slower job finding. Labour market dynamics obviously decline, but the effect on the unemployment rate is ambiguous.[7]

The effects are more complex when considering regions (for example, counties) and allowing workers to commute between neighbouring regions.[8] Younger workers are regional more mobile than older workers, and highly educated workers are more mobile than low-educated workers. To accommodate this empirical observation, we focus on regional labour market interactions.

The search rate $\sigma = u + e$ is the sum of unemployed and employed job seekers divided by the labour force, with $e \leq 1 - u$. From a regional perspective, it is obvious that people apply not only for jobs in their home region but also in surrounding regions. In this case, workers commute between their home and workplace region. We refer to commuting and inter-regional searches as mobility; hence, this definition excludes moves from one region to another. To maintain the model's simplicity, we consider job seekers and vacancies only from the local region l and regions adjacent to l, which we treat as one homogenous region, n.

The tightness (θ) of the local labour market is given by

$$\theta^l = v^l / \left(u^l + e^l + \tilde{u}^n + \tilde{e}^n\right) = v^l / \left(\sigma^l + \tilde{\sigma}^n\right),$$

and the tightness of the adjacent districts' labour market is given by

$$\theta^n = v^n / \left(u^n + e^n + \tilde{u}^l + \tilde{e}^l\right) = v^n / \left(\sigma^n + \tilde{\sigma}^l\right),$$

where v^l (v^n) denotes the local (neighbourhood) vacancy rate and $\sim$ represents spatial search activities. All job seekers apply for jobs in their home region. Because younger workers and more educated workers are more mobile, the number of regional mobile job applicants depends on the age and education structure of the job seekers. Only some of the older and low-educated job seekers from neighbouring regions apply for jobs in the local region. We refer to $\sigma^l = p^l \sigma_1^l + \left(1 - p^l\right) \sigma_2^l$ and $\sigma^n = p^n \sigma_1^n + (1 - p^n) \sigma_2^n$ as local search rates and $\tilde{\sigma}^n = \left[p^n \sigma_1^n + (1 - p^n) \sigma_2^n \alpha\right] \frac{L^n}{L^l}$ and $\tilde{\sigma}^l = \left[p^l \sigma_1^l + \left(1 - p^l\right) \sigma_2^l \alpha\right] \frac{L^l}{L^n}$ as spatial search rates.

[7] Burgess (1993) and Pissarides and Wadsworth (1994) found evidence for Great Britain that job separation rates are higher for young workers. In their study on England and Wales, Coles and Smith (1996) argued that matching may decrease with an older working population.

[8] The following approach is related to Ochsen (2021).

All workers resident in the local region, L^l, are normalised to 1. The rate $\tilde{\sigma}^n$, related to the labour force in the local labour market, has the same denominator as σ^l. $\tilde{\sigma}^n$ and σ^n differ because they are related to different labour force sizes, $\tilde{\sigma}^n$ to L^l and σ^n to L^n. The share of group 2 (low-educated or older workers) job seekers is larger in their resident region. The mobility weighting factor α, with $0 \leq \alpha < 1$, accommodates the limited spatial mobility of older and low-educated workers; hence, $\sigma_2^n > \sigma_2^n \alpha$. The differences between $\tilde{\sigma}^l$ and σ^l are analogous. This affects the distribution of the job seekers available to local firms: $p^l \frac{\sigma_1^l}{\sigma^l + \tilde{\sigma}^n} + p^n \frac{\sigma_1^n}{\sigma^l + \tilde{\sigma}^n} \equiv \bar{p}^l$. Hence, the job seeker structure depends on the group distribution (education or age) of the labour force in both regions.

Job seekers from the local region find, on average, new employment at the rate $f_i^l(\theta^l, \bar{p}^l) + f_i^n(\theta^n, \bar{p}^n)$ because of the spatially mobile search activities. From this, it follows that the spatial correlation of unemployment rates is positive, and the (spatial) correlation of vacancy and unemployment rates is negative. Separations can differ across groups and regions.

Finally, the local labour force, L^l, can be subdivided into three groups: local unemployed u^l, residents employed in the local region $\omega^{l,l}$, and residents employed in the neighbour region $\omega^{l,n}$. Since $L^l = 1$, we have $u^l + \omega^{l,l} + \omega^{l,n} = 1$.

The local unemployment rates of a group evolve according to separation and job finding, with $i = [y, o]$ or $i = [\mu, h]$:

$$\dot{u}_i^l = s_i^l \left(1 - \omega_i^{l,n} - u_i^l\right) + s_i^n \omega_i^{l,n} - f_i^l(\theta^l, \bar{p}^l) u_i^l - f_i^n(\theta^n, \bar{p}^n) u_i^l.$$

$s_i^l \left(1 - \omega_i^{l,n} - u_i^l\right)$ is the group-related flow into unemployment from local employment. $s_i^n \omega_i^{l,n}$ is the group-related flow into local unemployment from jobs in the neighbouring region. On the right-hand side, the last two terms are the probabilities of transition into a new job in the local and neighbouring labour market.

With $\dot{u}_i = 0$ and the summation of the two unemployment rates weighted at the respective local population proportions, p^l and $(1 - p^l)$, we obtain the local equilibrium unemployment rate:

$$\begin{aligned} u^l &= u_2^l + p^l \left(u_1^l - u_2^l\right) \\ &= \frac{s_2^l + \left(s_2^n - s_2^l\right) \omega_2^{l,n}}{s_2^l + f_2^l(\theta^l, \bar{p}^l) + f_2^n(\theta^n, \bar{p}^n)} + p^l \left(u_1^l - u_2^l\right), \end{aligned}$$

includes spatial and (spatial) group effects. The second term on the fraction line indicates that local unemployment increases as the number of spatially mobile workers increases and $s_2^n > s_2^l$, with $\omega_2^{l,n}$ as the share of residents employed in the neighbouring region (n). There are two channels for the group-related effects: the first effect is "hidden" in the (spatial) job-finding rates, and the second is related to the differences in group-related unemployment rates. This second term disappears if $u_1^l = u_2^l$. For $u_1^l > u_2^l$ ($u_1^l < u_2^l$), an increasing proportion of group 1 workers increases (decreases) overall separation and unemployment. The first effect contains group-related matching efficiency and mobility effects on the neighbouring labour market. This effect means that the more group 1 workers are in the neighbouring region, the lower the local market tightness and, hence, the lower the probabilities of transition into a new job for local workers ($\bar{p}^l$ is the share of job seekers available to local firms). Thus, the proportion of group-specific workers in the local and surrounding labour markets is important to the local unemployment rate. In the empirical part, we estimate regional panel data with a spatial panel model to analyse this empirically.

4 Empirical Analysis

This section analyses the relationship between changes in age and education composition of the labour force and the unemployment rate using data for Germany. The previous section shows the stock and flow data provided by the German Federal Employment Agency (Table 1). In this section, we first discuss the development of the groups that are considering using OECD data for Germany. The education groups are now differentiated by the ISCED classification, which is slightly different from the German Federal Employment Agency classification. Figure 1 provides the evolution of two age group shares and two education group shares for 1999-2018. The shares of prime-age workers (25-49 years) and medium-educated (ISCED 3-4) are not displayed.

The trend in the data shows that the shares of the younger and low-educated decline over time, while the shares of older and highly-educated workers increase. Given that the unemployment rates of older and highly educated workers are lower, these shifts must decrease the overall unemployment rate. Focusing only on the youth or low-educated workers, as typically done in the literature, is misleading because trends in other groups are not considered. The evolutions of German unemployment rates for age and education groups are provided in the Appendix (Figure 2 & 3).

Figure 1 about here

Based on this comparison, analysing the relationship between different age and education groups and unemployment appears meaningful. Since the analysis of macroeconomic data would provide no substantial new findings, regional data will be applied because they allow for considering a more differentiated pattern. Therefore, the econometric analysis will utilise county-level data (NUTS-3 level).

4.1 Data and Econometric Framework

We use the German Sample of Integrated Labour Market Biographies (SIAB-7514), a random sample drawn from the Integrated Employment Biographies (IEB). This data source entails individual data on labour market biographies.[9] Covering 16 years from 1999 to 2014, we converted the raw data into monthly segments. Hence, we analyse the period from January 1999 until December 2014. We computed our variables at the individual level and aggregated them at the administrative district level. This gives us a strongly balanced panel consisting of 402 cross-section units (counties) and 77,184 observations for different shares of the local labour force. We refer to Appendix A for a detailed description of the editing process.

Table 2 describes how the variables are generated and provides a summary statistic for these variables. We will use the age group shares in different combinations to deal with different reference groups. The two different types education and schooling will be used separately. Education is related to formal education after schooling and consists of no apprenticeship, apprenticeship, and academic degree. Schooling is related to the last school leaving certificate and is separated into no certification, certification without a university entrance qualification, and high school degree. In both cases, the reference in the regressions is the medium group (in terms of schooling, it is certification without a university entrance qualification, and in terms of education, it is apprenticeship).

We consider only employed and unemployed individuals of the working-age population between 15 and 64 years. This is related to the retirement age in Germany. In addition, we do not consider other individual characteristics like gender or work experience. Also, we abstain from interacting age with education groups, such as subdividing the youth into three groups: youth without apprenticeship, youth with apprenticeship, and youth with academic degrees.[10] This is caused by the limited number of individuals at the regional level. In some cases, we would not have enough individuals within a specific subgroup for our econometric analysis. Therefore, we decided to use only age groups and education groups in the labour force.

Table 2 about here

We are primarily interested in the effects of a change in group compositions in the local and neighbouring regions on local unemployment. For example, the local youth

[9] We use the weakly anonymous version of the Sample of Integrated Market Biographies (SIAB-7514), provided by the Research Data Centre (FDZ) of the Federal Employment Agency at the Institute for Employment Research (IAB). The data access was provided via on-site use and, subsequently, remote data access (Antoni et al. (2016)).

[10] In particular, the group of youth with academic degrees would not make much sense because many young people under 25 years have not finished their education. Hence, their education potentiality would be underestimated.

share captures group-specific job finding and separation in the local region. In addition, we consider the effect of changes in youth share in the neighbouring region on local unemployment. Since the youth in both regions hold, on average, the same job-relevant characteristics, we do not argue that, e.g., the youth in neighbouring regions is more productive than those in the local region. This is not possible because, in the estimates, every share is considered as a local region and as a neighbour region (I am the neighbour of my neighbour). However, the neighbouring region's youth needs to be spatially mobile (in terms of commuting) to work in the local region.[11] This is why we want to consider the youth share's effect of both the local and the neighbouring regions on local unemployment in the estimates. In addition, we also want to control for other age groups to differentiate between these groups and the reference group of older workers. For education, we argue in the same way. Here, we expect that the low-educated group is less mobile. Since this group is often small, we use the medium-educated group as a reference. To consider all these aspects, we use a flexible spatial econometrics approach: The spatial Durbin model. In the following, we describe the structure of the model.

To account for additional unobserved time and spatial varying effects at the local level, time lagged and spatial lagged effects of the dependent variable $\ln u_{it}$ (unemployment rate in logarithm) are considered (eq.2). To generate spatially lagged counterparts, we constructed a spatial weight matrix, W, that indicates the contiguity of regions and defined contiguity between two regions as those that share a common border. The matrix has the entry 1 if two regions share the same border and 0 otherwise. Then, we row normalise W, which ensured that all weights were between 0 and 1 and that weighting operations can be interpreted as an average of the neighbouring values.

$\ln u_{i,t-1}$ is the time lagged dependent variable and γ the autoregressive time dependence parameter. $W \ln u_{it}$ generates the average values of the regions adjacent to region i, and λ is the spatial dependence parameter - the spatial lagged effect of the dependent variable. $W \ln u_{i,t-1}$ is the combined spatial and time lagged dependent variable, and π is the spatio-temporal diffusion parameter. The inclusion of the spatial and time lagged dependent variable could serve as a control for omitted variables or at least reduce omitted variable bias (LeSage and Pace (2009)). We will discuss the issue of endogeneity in section 4.4.

To sum up, we consider a spatial and time dynamic model that is also known as the dynamic spatial Durbin model (with time and fixed effects):

[11] We distinguish this from the fact that they could move to the region where they work because, in this case, they live and work in the same region. According to the German Federal Employment Agency, in 2021, about 40% of all employed work and live in different countries.

$$
\begin{aligned}
\ln u_{it} &= \gamma \ln u_{i,t-1} + \lambda W \ln u_{it} + \pi W \ln u_{i,t-1} \\
&+ \alpha_1 \ln agegroup1_{it} + \beta_1 W \ln agegroup1_{it} \\
&+ \alpha_2 \ln agegroup2_{it} + \beta_2 W \ln agegroup2_{it} \\
&+ \alpha_3 \ln edugroup1_{it} + \beta_3 W \ln edugroup1_{it} \\
&+ \alpha_4 \ln edugroup2_{it} + \beta_4 W \ln edugroup2_{it} \\
&+ c_i + \theta_t + \epsilon_{it}
\end{aligned} \tag{2}
$$

where $\ln u_{it}$, $\ln agegroup_{it}$, $\ln edugroup_{it}$ and ϵ_{it} are stacked $Tn \times 1$ column vectors, W is a row normalized $n \times n$ spatial weights matrix that is nonstochastic and generates the spatial dependence between cross-sectional units, c_i are regional, and θ_t are time effects. $\ln agegroup1$ is the share of the first age group (e.g. youth) in the local region, and $W \ln agegroup1$ is the average share of the same group in the neighbouring regions. The same applies to the second age group and the two education groups ($edugroup$).[12] The bias-corrected quasi maximum likelihood approach provided by Yu et al. (2008) is considered for the dynamic models.[13] The effects of the time and spatial lagged dependent variable will not be discussed below.[14] However, these lags help afterwards to calculate the dynamic long-run effects. In all regressions, county-cluster robust standard errors are considered.

The parameters α and β in eq. (2) cannot be interpreted as elasticities or partial derivatives due to spillover effects.[15] Therefore, we first provide the estimated coefficients and, subsequently, the resulting elasticities. Because of their limited mobility, not all older workers or less educated workers in the neighbouring region apply for jobs in the local region, and therefore, the spatial group shares serve mostly as a proxy variable for mobility in terms of commuting.

For example, let us assume that prime-age workers are more attractive to firms than other age groups. An increase in the neighbouring prime-age share induces more job applications at firms in the local region. This, in turn, decreases search costs and increases the vacancy rate. However, this also decreases the local market tightness and the probability of transitioning into a new job for local job seekers. This effect is likely larger than the

[12] In contrast to the shift-share approach, which has also been used in the literature to account for changes in the age structure, the considered model is more flexible. In particular concerning regional interactions.

[13] All spatial regressions are estimated using STATA and the xsmle code.

[14] Using OLS based methods instead would produce biased coefficients for the time and spatial lagged effects of the dependent. See, for example, Nickell (1981) for the asymptotic bias of OLS estimation using the time lagged effect and Kelejian and Prucha (1998) for information on biased OLS estimates when spatial lagged effects are considered.

[15] See, for example, LeSage and Pace (2009) for a detailed discussion.

effect on vacancies (more jobs). With respect to the parameter β, we expect a positive effect. In contrast, the parameter α is negative if the local share of prime-age workers increases, and this age group is more attractive to firms overall.

If the spatial effects of the considered group structures are essential, we have to consider the bias on α if we neglect β. Let ω be the parameter for the local effect when the spatial effect is neglected. The standard result is then $\omega = \alpha + \beta\delta$, where δ measures the covariance of the local and the spatial age or education structure. The latter is positive in the data, and we expect β to be positive, which yields a positive bias on ω.

Concerning the statistical relevance of our estimates, we provide county-cluster robust standard errors to control for heteroskedasticity, serial correlation and cross-sectional dependence in the residuals. We consider the False Positive Risk (FPR) to provide information for statistical evidence. In contrast to p-value, the FPR measures the probability of the null hypothesis being true (Colquhoun 2019 and 2017). For a discussion of the misinterpretation of p-value, see, for example, Wasserstein and Lazar (2016). We consider FPR = 0.05 (equals p-value of 0.0034) and FPR = 0.01 (equals p-value of 0.0005). For the computation of the FPR, we refer to Appendix B.

4.2 Results

Table 3 provides different basic specifications of equation (2). For reasons of comparison, regressions (1), (5), and (9) are simple fixed and time effects models. In regressions (2), (6), and (10), only the spatial lagged dependent is considered ($\gamma = \pi = 0$), while in (3), (7), and (11), the time lagged effect is also included ($\pi = 0$). In (4), (8), and (12), all lagged effects of the dependent are considered. Since all spatial and time lagged effects provide strong empirical evidence, we prefer (4), (8), and (12) as the best specification.[16] We consider only one group in these estimates because the focus here is on model specification in general. However, a short discussion of the results will help us relate our findings to the existing literature. The estimated elasticity of the standard fixed and time effects estimates can be compared with the long-run elasticities provided below. While (1) and (5) are in line with the literature, regression (9) provides no reliable estimates. This is because the share of those who graduate without a school leaving certificate is very small (about 1 per cent). Therefore, the results of regression (9)-(12) will not be interpreted further.

Concerning regressions (2) to (4), we find empirical evidence for the local effect of the youth share on unemployment. Due to the strong empirical evidence for lagged dependent effects, we rely most on regression (4). In this case, the spatial effect of the youth share provides no empirical evidence. The regressions (6) to (8) consider formal education.

[16] Finally, we test this specification against a spatial autoregressive model and a spatial error model and find strong empirical evidence favouring the preferred dynamic spatial Durbin model.

Independent of the specification, we find that the local share of those in the labour force with no apprenticeship is positively related to the unemployment rate, while the spatial effect is negative. Hence, compared to the reference group, this group is less attractive to firms.

Table 3 about here

Table 4 considers groups of different ages and formal education (without apprenticeship, with apprenticeship, academic degree). In addition to the youth share, a second and third age group is added with different age group ranges and reference groups. We do this to additionally control for possible interactions between the education and age groups.[17] The educational reference is always the group with apprenticeship.[18] While we find empirical evidence for the local youth share effect in all specifications, the spatial effect is not statistically relevant. For the age group 25 to 39 years, we find neither empirical evidence for the local nor spatial effect.[19] When the reference age group is 50 -64, the age group 25-49 has a positive spatial effect (regression (3)). In regression (4), we subdivide this age group into 25-39 and 40-49 years. Here, we find positive empirical evidence only for the spatial effect of the age group 40 to 49 years. Older prime-age workers (40-49 years) seem to be more mobile and competitive than the reference (50-64 years) and affect the market tightness.[20] In addition, when we consider the direction of all age cohort effects between 25-49 years, the local effects are negative, while the spatial effects are positive. This finding indicates that this age group is more attractive than the reference cohort. We find the opposite direction of the effects for the youth, which means that the reference is more attractive to firms than the youth.

Workers without formal apprenticeships seem less attractive to firms and raise local unemployment. In addition, the share of this group in the neighbouring regions is negatively related to the local unemployment rate. We argue that this reflects the decreasing share of spatially mobile workers with apprenticeship (reference). The opposite applies to workers with an academic background. The local effect is in line with our argument above (more attractive than the reference group), but the empirical evidence is weak, and the spatial effect reflects competitive pressure due to the mobility of these workers. Further economic interpretation will be conducted using the elasticities below. For the parameters γ, λ, and π, we find that they collectively pass the stationarity conditions

[17]Due to multicollinearity, estimates with more age group shares are not advantageous.

[18]Regressions with age or education only are provided in the Appendix.

[19]On the one hand, it is possible that the local difference between young prime-age workers and older workers is too small to be statistically important at the local level. On the other hand, it is also possible that opposing effects cancel out each other. For example, the overall effect can be small if younger prime-age workers undertake job searches more intensively, but older workers are more productive.

[20]Of course, the cut at the age of 40 years is somewhat arbitrary, and it could also be at the age of, for example, 38 or 42. The age groups considered for this were chosen for technical reasons.

(Baltagi et al. (2018) and Debarsy et al. (2012)): $\lambda+\pi \geq 0$; $|\gamma|+(\lambda+\pi) < 1$; $\lambda-\pi < 1$; $\gamma-(\lambda-\pi) > -1$.

Table 4 about here

Table 5 provides the same specifications as Table 4, but we now consider different schooling degrees instead of formal education. The reference group is secondary education. Most of the coefficients are similar to the estimates provided in Table 4. However, the share of workers with no school leaving degree (dropouts) does not affect local or spatial unemployment. As pointed out above, the share of those who graduate without a school leaving certificate is very small. Hence, we treat the estimates as not reliable. The optimistic interpretation is that this group is too small to affect the overall unemployment level substantially. The results in Table 5 indicate stationarity and dynamic stability.

Table 5 about here

4.3 Interpretation

For the group crowding effect, we argue that the above-provided theory of age or education group differences in job finding and separation matters, not (only) the group size alone. Technical change has increased labour market opportunities for educated workers and reduced job opportunities for low-educated workers. For periods of demographic change (age and education), the results provide strong evidence that age and education group-related differences in labour market characteristics are an important driver of the overall unemployment change.

To interpret the estimates, we calculate direct (local) and indirect (spatial) as well as short-term and long-term effects.[21] The direct effect measures the change in the dependent variable due to changes in the same region's explanatory variable (averaged over all regions). In contrast, the indirect effect measures the dependent variable's change due to changes in the neighbour region's explanatory variable (averaged over all regions). The direct and indirect effects add up to the total effect. The short-term effects quantify the dependent variable response in each region at time t to changes in the explanatory variables at time t. The long-run effects cumulate the dependent variable responses over time to changes in the explanatory variables at time t. The marginal effect will be calculated for each time unit and decay over time. Since this takes some years, the cumulative long-term effects are larger in magnitude than the contemporaneous short-term effects.

Table 6 provides elasticities for selected regressions of Table 4 (elasticities for regressions of Table 5 are provided in the Appendix).[22] In principle, short-run elasticities are

[21] See Belotti et al. (2017) for a more detailed discussion.

[22] The effects are calculated according to Elhorst (2014) and are averages over 500 Monte Carlo replications (LeSage and Pace (2009)).

smaller than long-run effects. Direct, indirect, and total effects are inelastic even in the long run. Concerning the youth share, it turns out that substituting the reference group 50-64 years is less costly in terms of unemployment (0.3) than the substitution of the reference group apprenticeship by those without an apprenticeship (0.6). These findings emphasize the difference in labour market characteristics of groups. However, both elasticities are mainly driven by the direct effect since the indirect effects are not statistically evident. The elasticities of the fixed effects estimates reported in Table 3 (regressions (1) and (5)) are between the short-run and long-run elasticities. Hence, applying the spatial Durbin model provides new insights for discussing the size of elasticities.

We find empirical evidence for an indirect effect for older prime-age workers (40-49 years) and more educated workers. This means that well-educated workers from surrounding areas compete with the locals for jobs in the local region. The positive elasticity for *academics* (0.5 for regression (2) and 0.3 for regression (4)) implies that the local worker's job-finding rate declined. The situation is similar when many older prime-age workers are in the surrounding area. One interpretation is that these workers are experienced and mobile compared to the group 25-39 years (less experienced) and the reference 50-64 years (less mobile). In addition, the shares of more educated and older prime-age workers have no local effect, even in the long run. Hence, both shares can increase at the expense of the reference group, which causes no effect on local unemployment but adverse effects on unemployment in surrounding labour markets. From this, we can draw important conclusions. First, this is empirical evidence that the effects of local group crowding depend on the considered group's labour market characteristics. Second, these results are further evidence for the discussion above about the important role of spatial interactions in local labour markets. Third, these are substantial arguments for empirical analysis at the local (county) level because spatial interactions cannot be considered (adequately) at the national or state level.

Overall, the results reflect that the youth and less educated workers positively affect the local unemployment rate but do not induce spatial effects due to low competitiveness. In contrast, a rising share of older prime-age workers and more educated workers means that more (mobile) workers are available for jobs in the neighbouring district. This, in turn, decreases market tightness to the disadvantage of local job seekers. Hence, considering spatial interactions is essential to explain the dynamics of local unemployment rates. Based on the estimates, the ageing of the labour force reduces the share of regional mobile workers, and this reduction decreases the local unemployment rate. In contrast, the shift to more highly-educated and fewer low-educated workers increases the share of regional mobile workers and causes opposing effects on local unemployment.

Concerning the latter finding, we argue that this is in line with the literature on the decline in routine task-intensive jobs (Autor and Dorn (2009, 2010), Acemoglu and Autor (2011)). Routine employment is predominantly performed by workers with an apprenticeship (reference group). The spatial effect of the highly educated group can be interpreted as a supply shock to a local labour market because the local group shares are unchanged. This would also be in line with structural occupational crowding (Gesthuizen and Wolbers (2010), Klein (2015)). To analyze the estimated effects further, we consider the actual changes in the groups in the period considered.

Table 6 about here

We now use the group's elasticities and rate of change to assess the strength of group effects on the overall unemployment rate for the period considered. Table 7 provides in column (a) the overall average changes between 1999 and 2014 in %. The cumulative percentage change of the unemployment rate due to total short-run and total long-run effects is provided in (b) and (c).

For example, according to regression (2) in Table 4, the long-run effect of ageing on the unemployment rate is -7.55 per cent. For education, we find larger but opposing effects from the decline of workers without an apprenticeship and the increase of workers with an academic background. Overall, the long-run effect of the rise in education is -5.37. Hence, according to regression (2), the overall long-run effect is -12.92 per cent. Related to the average unemployment rate in the period considered, this equals 1.3 percentage points.

When we consider regression (4), we find stronger effects. The overall long-run effect is -27.39 per cent and consists of a -12.97 per cent age groups effect and -14.42 per cent education groups effect. This equals a decline in the unemployment rate by about a quarter. Although the older prime-age workers' elasticity in Table 6 is the largest, the change in the group size has a minimal effect. Overall, the group size changes in age and education substantially affect the local unemployment rate. The baby-boomer cohort has entered the last age group in the labour force and moves on to retirement age, leading to a decline in the overall unemployment rate. The decline in the share of less-educated workers mitigates unemployment development, while the rise in the highly educated workers' group increases the unemployment risk of the apprenticeship group.

Table 7 about here

4.4 Robustness

The effect of a group on the unemployment rate might suffer from endogeneity bias. For example, young or more educated people will likely migrate to regions with relatively low unemployment rates. Such migration flows can cause a spurious correlation between unemployment rates and the group, foster ageing and brain drain in regions with high unemployment rates, and decrease market tightness (increase unemployment) in the preferred region. However, Shimer (2001) concludes that instrumental variable estimates do not yield statistically different results, and in some cases, it turns out that the youth share is not endogenous. Biagi and Lucifora (2008) come to similar conclusions. Another bias can be caused by discouraged workers, for which Biagi and Lucifora (2008) find only weak evidence.

As highlighted earlier, our study takes a unique approach by considering the spatial and time lagged dependent variable in eq. (2) as a control for omitted variables or at least to reduce omitted variable bias.[23] Additionally, we deviate from the existing literature by examining a more detailed pattern of the age and education structure. This allows us to control for group size shifts of more than one group, providing a further step to reduce omitted variable bias.

Concerning the correlation pattern, we compare the one-year lagged change in the log unemployment rate with the change in the log of the youth group, the group of older workers, the group of those without an apprenticeship, and the group of academics (see Figures in the Appendix).[24] When regional migration matters, the youth or more educated group should cause a negative correlation in this relationship. In this case, the slope will become negative because a decline in the unemployment rate would be associated with a rise in the youth or more educated group (and vice versa). However, the correlation pattern for all four groups is very low.[25] This is no evidence that migration does not matter, but it shows that other effects could be more substantial.

Our regression model incorporates a spatial weight matrix that defines contiguity between two regions as those that share a common border. Commuting into regions that are farther away is not considered. Therefore, we estimate the model using second-order contiguity and consider the neighbour's neighbours. The estimates are provided in the Appendix and are directly comparable to Table 4. Importantly, the results remain consistent, demonstrating the robustness of our findings. The spatial parameters are slightly larger in magnitude, leading to slightly larger indirect elasticities. This is expected, as the increased area of the neighbouring region affects market tightness in the local region, potentially disadvantaging local job seekers.

5 Conclusions

In this article, we examined the relationship between the (spatial) age and education structure of the labour force and unemployment at the regional level based on a spatial

[23] An IV specification (e.g., two-stage dynamic spatial Durbin model) seems difficult and beyond this paper's scope.

[24] Dots and the solid line represent the whole sample, the short dashed line shows the relationship for regions with unemployment rates above 15.5%, and the long dashed line represents regions with unemployment rates below 4.4%.

[25] In addition, we estimate fixed effects regressions and find no empirical evidence.

Durbin model structure of the econometric model. Based on a theoretical model, we argue that labour market groups (age or education) differ in job finding, separation, and mobility in terms of commuting. Because of these differences in their labour market characteristics, the current changes in the labour force distribution reduce the overall unemployment rate. The period 1999-2014 in Germany is characterised by an ageing process and a rising education level of the labour force.

Concerning local effects, we find empirical evidence that a rising share of youth or low-educated workers increases unemployment. For these groups, we do not identify spatial effects. However, the share of older prime-age or more educated workers in the surrounding area positively affects the local unemployment rate. In addition, these groups do not raise their local unemployment rates. This is empirical evidence that local group crowding depends on the considered group's labour market characteristics. We argue that the spatial educational group crowding is related to the decline in routine task-intensive jobs. Finally, we find that the current group changes (age and education) account for reducing the unemployment rate by almost 25 per cent.

Our results are further evidence of the substantial role of regional interactions between local labour markets, and we suggest focusing more on the empirical analysis at the local (county) level. Future research could focus more on the interaction of age and education, birth cohorts, and the effects of the current skilled labour shortage. These issues are beyond the scope of our analysis.

Regarding policy conclusions, labour market policies or programs should be focused on supporting individual occupational mobility. Hence, group and job characteristics are more important than differentiating between urban and rural areas. Overall, the ongoing ageing and rise in the average education level will reduce German unemployment in the future.

6 Appendix

6.1 A: Data Description

We use the Sample of Integrated Labour Market Biographies (SIAB-7514) panel, a 2 per cent random sample drawn from the Integrated Employment Biographies (IEB) of the Institute for Employment Research (IAB). The IEB allow to track the employment status of a person daily and consists of all individuals in Germany who are characterized by at least one of the following employment status: employment subject to social security (in the data since 1975), marginal part-time employment (in the data since 1999), benefit receipt according to the German Social Code III or II (SGB III since 1975, SGB II since 2005), officially registered as job-seeking at the German Federal Employment Agency or (planned) participation in programs of active labour market policies (in the data since

2000). These data come from different sources and are merged in the IEB. The suffix 7514 stands for the panel version covering 1975 until 2014, with both years included in the panel.

Our main goal was to reshape the raw data in a way that enabled us to distinguish between employment and unemployment at the administrative district level (cross-section) monthly (time unit) throughout the entire period of the analysis. We use the territorial allocation from 31.12.2014 for our analysis, which means we have 402 cross-section units (Kreise). We analyze the period from January 1999 to December 2014, 192 months.

Defining employment and unemployment was the first step towards achieving this particular panel structure. Since the SIAB-7514 consists of individual data in its raw version, we define an individual as employed if and only if the individual reports the characteristic attribute 101 in the employment status variable. In turn, an individual is deemed unemployed if and only if it reports one of the characteristic attributes 1,2,31,32,41,51 in the employment status variable.[26]

To aggregate the individual data to a monthly administrative district level, we had to edit the original panel substantially. In the first step, we convert the raw data to sequential data. The SIAB is organized in spells. Each spell has a commencing date and an end date, which are precise to the day. The dates mark the beginning and the end of an individual episode. The term "precise to the day" implies that a spell may start and end on any given day in any given month in any given year between January 1999 and December 2014. In the raw version, spells can overlap with each other. Hence, spells for the same individual may cover the same period or overlap in part. Therefore, creating sequential data means organizing the spells so that there will a) be no congruency or partial overlapping and b) that each spell starts exactly one day after the end date of the previous spell if the same individual is considered. We took the STATA code to generate sequential data from the data report for the SIAB-7514.[27]

Once the sequential data structure was established, we created a variable reporting the single year of the individual spell using the year specified in the variable that marked the beginning of an episode and erased all spells that started and ended before 1999. Next, we pay attention to those spells that overlapped years. That is spells that started in one year and ended in the following year or the year after that. We focus solely on spells that cover a maximum two-year span based on the year reported in the column for the start date of the episode. All spells exceeding this limit were dropped from the panel. This is because the actual number of these spells is very small. Less than 3 per cent of the entire panel is affected. Since these spells almost exclusively report attributes in the variable

[26]For a detailed definition of the attributes, please refer to Frequencies and Labels of the SIAB-7514 data report. A comprehensive list of all possible attributes of the variable defining the employment status can be found in the file *"Labels SIAB 7514 v1 de.log"*.

[27]For a detailed description of the applied code, please refer to pages 27 and 28 of the data report.

depicting the employment status we do not use for our analysis, almost all those spells are dropped later. The remaining spells, which overlapped one year or more, are split into several episodes to attach a unique value for the year variable to each episode. We then drop those spell episodes that started before 1999. For example, if a spell started in 1998 and ended in 2000, we duplicated the original spell two times, ending with three identical spells. Each spell is assigned to a year, i.e. 1998, 1999, and 2000. We kept the two latter spells and dropped the first. Once the spells are in order, we split the panel into individual years, effectively giving up the panel structure.

In the next step, we develop a code that enables us to brand an individual as employed or unemployed in any given month from January 1999 to December 2014. We employ a syntax that operates in a way that an individual is assigned to the status of being employed or unemployed for a given month if the individual status exceeds half of a given month. For example, a person reports an episode of employment in a given year that starts on January 1st and ends no later than March 15th. This person is assigned to be employed throughout January and February of that year. For March, however, the individual could be assigned either status. In March, an individual will be employed if the consecutive episode starts the day after the previous episode and experiences a change in any variable, but the variable indicates the employment status. On the other hand, an individual is unemployed in March if the variable indicates a change in employment status from 101 to any number in 1,2,31,32,41,51.

We create our variables once we have transformed the individual episodes into monthly episodes. We recode the original industry branches in the panel by categorizing them into 13 branches of economic activity using the standards provided in the FDZ data report of the Sample-of-Integrated-Labour-Market-Biographies Regional-File 1975-2010 (SIAB-R 7510).[28]

We computed the respective shares of employment and unemployment for each combination of cross-section and time unit for all variables. Finally, we aggregate the individual data at the administrative district level and receive a strongly balanced panel, which is the basis of our empirical analysis.

6.2 B: Computation of the False Positive Risk

The false positive risk (FPR) was introduced by Colquhoun (2019, 2017) and measures the probability that the result occurred by chance $P\left(H_0 \mid data\right)$. The approach is based on the Bayes theorem that we express in odds:

$$\text{posterior odds on } H_1 = \text{Bayes factor} \times \text{prior odds}$$

This is equal to

[28]For more details we refer to Table A7 on pages 57-58.

$$\frac{P(H_1 \mid data)}{P(H_0 \mid data)} = \frac{P(data \mid H_1)}{P(data \mid H_0)} \times \frac{P(H_1)}{P(H_0)}$$

Following Colquhoun, the Bayes factor becomes a likelihood ratio (LR), and the prior odds can be expressed using the probability that there is a real effect, $P(H_1)$: $P(H_1) / (1 - P(H_1))$. Among others, Sellke et al. (2001) provide an approach to calculate the LR based on the p-value: $LR = 1/(-ep\log(p))$. However, this measure can be considered only as long as $p < 1/e$, with e as Euler's number.

Taking things together and considering $P(H_0 \mid data) = 1 - P(H_1 \mid data)$ gives us the FPR:

$$FPR = \frac{1}{1 + \frac{1}{-ep\log(p)} \frac{P(H_1)}{1-P(H_1)}}$$

Applying the FPR approach requires to specify $P(H_1)$ first. However, specifying the prior probability in regression analysis is difficult, and we should always be careful when defining this unknown number. We use $P(H_1) / (1 - P(H_1)) = 0.5/(1 - 0.5) = 1$, which means that both probabilities have the same weight. This is equal to a 50:50 chance for a real effect specified before the data are analyzed. This seems reasonable when we do not know what to choose or are open to the results. When the prior probability of a real effect is 0.5, the FPR is much larger than the corresponding p-value, and, for example, $p = 0.05$ is equal to a FPR of 0.2893.

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8 Figures and Tables

Table 1: Average Flow Rates and Unemployment Rates in Germany

	separation rate	job finding rate	u_i^*	u_i
youth	0.038	0.416	8.4	8.1
older workers	0.018	0.172	9.8	10.2
low educated	0.073	0.216	25.7	25.7
high educated	0.011	0.25	4.3	4.3
all	0.023	0.228	9.4	9.5

Notes: Monthly data are taken from statistics of the Federal Employment Agency. Job-finding rates are calculated as the ratio of flows from unemployment to employment in the previous month, and separation rates are calculated as flows from employment to unemployment in the previous month. Equilibrium unemployment rates are calculated according to equation 1, and the (normal) unemployment rate is calculated as the number of unemployed divided by the labour force. Period: January 2008 to December 2018.

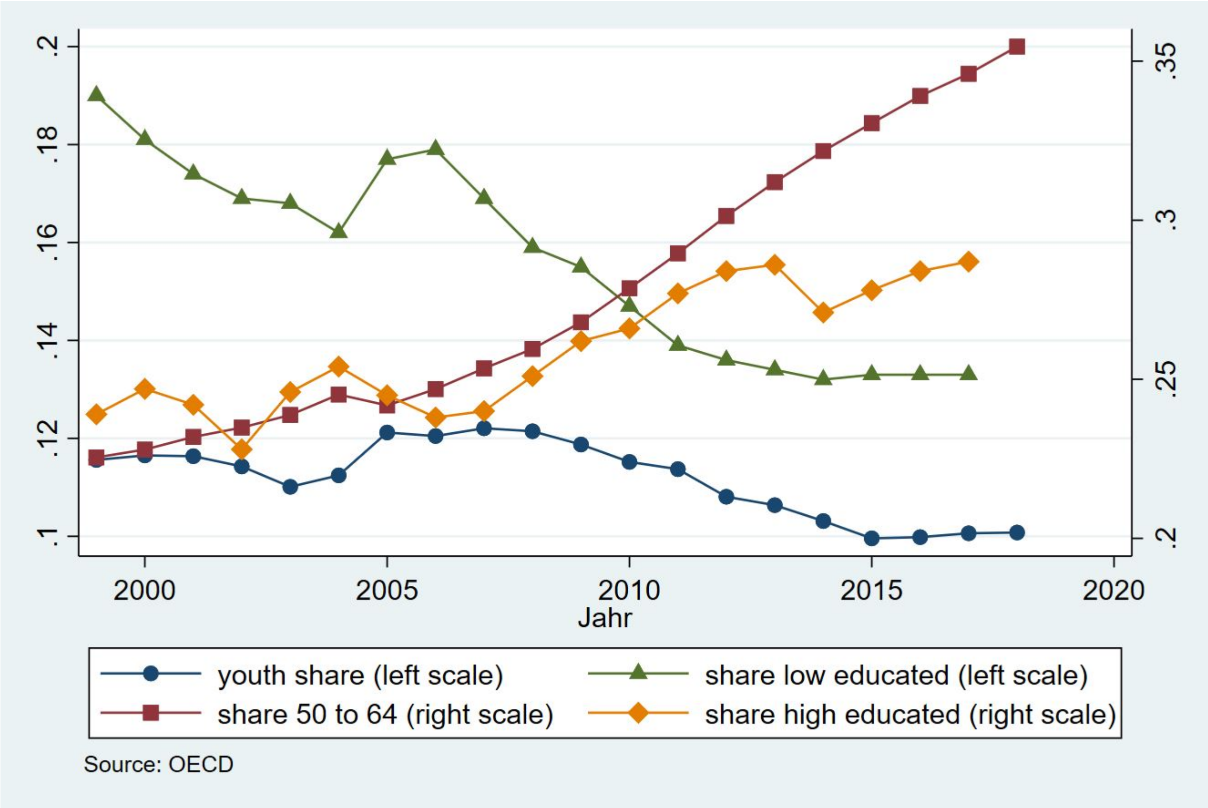

Figure 1: Labour Force Share for Age and Education in Germany

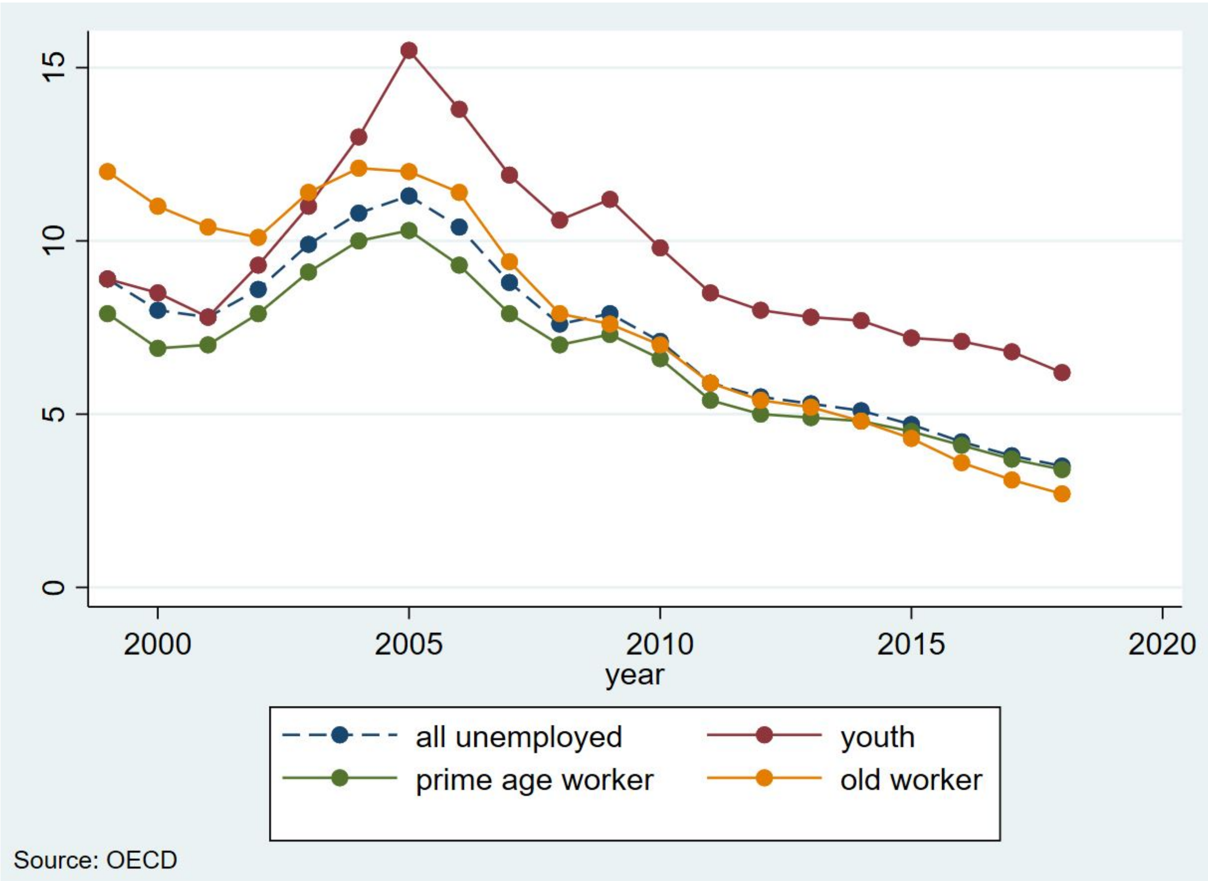

Figure 2: Unemployment Rates by Age Groups in Germany

Table 2: Variable Description and Basic Statistics

variable	description	obs	mean	se	min	max
unemployment rate	number of unemployed individuals in the district labour force to all individuals in the district labour force	77,184	0.0996	0.055	0.008	0.450
age groups						
youth	number of individuals in the district labour force aged 15 to 24 to all individuals in the district labour force aged 15 to 64	77,184	0.069	0.018	0.012	0.152
25-39 years	number of individuals in the district labour force aged 25 to 39 to all individuals in the district labour force aged 15 to 64	77,184	0.356	0.052	0.217	0.512
25-49 years	number of individuals in the district labour force aged 25 to 49 to all individuals in the district labour force aged 15 to 64	77,184	0.666	0.045	0.476	0.785
40-49 years	number of individuals in the district labour force aged 40 to 49 to all individuals in the district labour force aged 15 to 64	77,184	0.310	0.032	0.184	0.411
education/schooling groups						
no apprenticeship	number of individuals in the district labour force without vocational education to all individuals in the district labour force	77,184	0.134	0.057	0	0.337
academics	number of individuals in the district labour force with an academic education to all individuals in the district labour force	77,184	0.115	0.063	0.016	0.518
no graduation	number of individuals in the district labour force with no graduation to all individuals in the district labour force	77,184	0.013	0.010	0	0.090
high school	number of individuals in the district labour force with university entrance qualification to all individuals in the district labour force	77,184	0.183	0.092	0.030	0.691

Notes: Data are taken from the SIAB-7514 and aggregated to a balanced monthly county level from January 1999 to December 2014.

Table 3: Basic Results for Age, Education, and Schooling

	Dependent variable: log unemployment rate											
reference group:	age 25-64				at least apprenticeship				at least secondary education			
considered groups:	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
log youth	$0.193^{\ddagger}$	$0.123^{\ddagger}$	$0.037^{\ddagger}$	$0.039^{\ddagger}$								
	(0.016)	(0.013)	(0.003)	(0.003)								
W(log youth)		$0.078^{\dagger}$	-0.016	-0.005								
		(0.024)	(0.006)	(0.005)								
log no apprenticeship					$0.316^{\ddagger}$	$0.253^{\ddagger}$	$0.079^{\ddagger}$	$0.078^{\ddagger}$				
					(0.021)	(0.018)	(0.005)	(0.005)				
W(log no apprenticeship)						0.020	$-0.042^{\ddagger}$	$-0.030^{\ddagger}$				
						(0.031)	(0.008)	(0.007)				
log no graduation									0.002	0.001	0.001	0.001
									(0.003)	(0.002)	(0.001)	(0.001)
W(log no graduation)										$0.009^{\dagger}$	0.001	0.001
										(0.003)	(0.001)	(0.001)
spatial lag (λ)		$0.477^{\ddagger}$	$0.162^{\ddagger}$	$0.241^{\ddagger}$		$0.478^{\ddagger}$	$0.166^{\ddagger}$	$0.244^{\ddagger}$		$0.499^{\ddagger}$	$0.172^{\ddagger}$	$0.243^{\ddagger}$
time lag (γ)			$0.798^{\ddagger}$	$0.809^{\ddagger}$			$0.789^{\ddagger}$	$0.800^{\ddagger}$			$0.804^{\ddagger}$	$0.813^{\ddagger}$
spatial-time lag (π)				$-0.116^{\ddagger}$				$-0.113^{\ddagger}$				$-0.112^{\ddagger}$
within R^2	0.808	0.158	0.919	0.919	0.814	0.601	0.920	0.920	0.803	0.133	0.919	0.918
Observations	77,184	77,184	76,782	76,782	77,184	77,184	76,782	76,782	77,184	77,184	76,782	76,782

Notes: Spatial lag, time lag, and spatial-time lag refer to the dependent; all regressions include fixed and time effects; county-cluster robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county-level panel; †= FPR $\leq$0.05,‡= FPR $\leq$0.01.

Table 4: Results for Age and Education

	Dependent variable: log unemployment rate			
reference apprenticeship and age group:	25-64	40-64	50-64	
considered groups:	(1)	(2)	(3)	(4)
log youth	0.036‡	0.036‡	0.034‡	0.034‡
	(0.003)	(0.003)	(0.003)	(0.003)
W(log youth)	-0.013	-0.011	-0.007	-0.010
	(0.006)	(0.007)	(0.006)	(0.007)
log 25-39		0.002		-0.003
		(0.010)		(0.012)
W(log 25-39)		0.010		0.040
		(0.020)		(0.021)
log 25-49			-0.014	
			(0.020)	
W(log 25-49)			0.119‡	
			(0.038)	
log 40-49				-0.005
				(0.011)
W(log 40-49)				0.072‡
				(0.021)
log no apprenticeship	0.077‡	0.077‡	0.078‡	0.078‡
	(0.005)	(0.005)	(0.005)	(0.005)
W(log no apprenticeship)	-0.030‡	-0.030‡	-0.030‡	-0.029‡
	(0.008)	(0.008)	(0.008)	(0.008)
log academics	-0.009	-0.009	-0.009	-0.011
	(0.006)	(0.006)	(0.006)	(0.006)
W(log academics)	0.049‡	0.050‡	0.044‡	0.041‡
	(0.009)	(0.009)	(0.009)	(0.009)
spatial lag (λ)	0.240‡	0.240‡	0.240‡	0.239‡
time lag (γ)	0.796‡	0.796‡	0.795‡	0.795‡
spatial-time lag (π)	-0.120‡	-0.120‡	-0.122‡	-0.122‡
within R^2	0.919	0.920	0.920	0.920
Observations	76,782	76,782	76,782	76,782

Notes: Spatial lag, time lag, and spatial-time lag refer to the dependent; all regressions include fixed and time effects; county-cluster robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county-level panel; †= FPR ≤0.05,‡= FPR ≤0.01.

Table 5: Results for Age and Schooling

	Dependent variable: log unemployment rate			
reference secondary education and age group:	25-64	40-64	50-64	
considered groups:	(1)	(2)	(3)	(4)
log youth	0.041‡	0.043‡	0.040‡	0.041‡
	(0.003)	(0.003)	(0.003)	(0.003)
W(log youth)	-0.016	-0.016	-0.019†	-0.021†
	(0.006)	(0.006)	(0.006)	(0.007)
log 25-39		0.015		0.016
		(0.010)		(0.011)
W(log 25-39)		-0.001		0.023
		(0.020)		(0.022)
log 25-49			-0.016	
			(0.018)	
W(log 25-49)			0.082	
			(0.036)	
log 40-49				0.001
				(0.011)
W(log 40-49)				0.058
				(0.020)
log no graduation	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
W(log no graduation)	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)
log high school	-0.014	-0.014	-0.017	-0.019†
	(0.006)	(0.006)	(0.006)	(0.006)
W(log high school)	0.062‡	0.064‡	0.055‡	0.052‡
	(0.009)	(0.009)	(0.009)	(0.010)
spatial lag (λ)	0.239‡	0.239‡	0.238‡	0.238‡
time lag (γ)	0.808‡	0.808‡	0.806‡	0.806‡
spatial-time lag (π)	-0.119‡	-0.120‡	-0.124‡	-0.124‡
within R^2	0.897	0.899	0.918	0.918
Observations	76,782	76,782	76,782	76,782

Notes: Spatial lag, time lag, and spatial-time lag refer to the dependent; all regressions include fixed and time effects; county-cluster robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county-level panel; †= FPR $\leq$0.05,‡= FPR $\leq$0.01.

Table 6: Short-Run and Long-Run Elasticities: Age and Education

	short-run elasticities			long-run elasticities		
considered groups:	direct	indirect	total	direct	indirect	total
dependent variable: log unemployment rate						
Table 4: Regression (2): reference groups: with apprenticeship and 40-64 years						
youth	0.036	-0.004	0.032	0.186	0.123	0.308
	(0.003)	(0.008)	(0.009)	(0.018)	(0.101)	(0.112)
25-39	0.003	0.016	0.018	0.021	0.161	0.182
	(0.010)	(0.024)	(0.027)	(0.056)	(0.259)	(0.288)
no apprenticeship	0.077	-0.014	0.063	0.392	0.206	0.598
	(0.005)	(0.009)	(0.010)	(0.027)	(0.166)	(0.179)
academics	-0.006	0.060	0.054	-0.007	0.525	0.518
	(0.006)	(0.010)	(0.012)	(0.031)	(0.174)	(0.190)
Table 4: Regression (4): reference groups: with apprenticeship and 50-64 years						
youth	0.035	-0.002	0.033	0.177	0.116	0.293
	(0.003)	(0.008)	(0.009)	(0.018)	(0.097)	(0.107)
25-39	-0.001	0.051	0.051	0.009	0.444	0.463
	(0.012)	(0.026)	(0.028)	(0.060)	(0.270)	(0.296)
40-49	-0.001	0.088	0.087	0.028	0.755	0.783
	(0.011)	(0.024)	(0.023)	(0.054)	(0.260)	(0.275)
no apprenticeship	0.078	-0.013	0.064	0.393	0.189	0.582
	(0.005)	(0.010)	(0.011)	(0.029)	(0.155)	(0.171)
academics	-0.009	0.047	0.038	-0.030	0.372	0.343
	(0.006)	(0.011)	(0.013)	(0.032)	(0.130)	(0.146)

Notes: Direct effects come from the local region, and indirect effects come from the neighbouring regions. Long-run effects cumulate feedback over the period considered. Robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county level panel; observations: 76,782.

Table 7: Average Percentage Changes in Unemployment Rate

considered groups:	overall change rate (a)		effects of overall change rate: short-run (b)	effects of overall change rate: long-run (c)
Table 4, regression (2)				
reference: with apprenticeship and 40-64 years		overall	-1.42	-12.92
youth	-27.07			
25-39	-26.26	total age effect	-0.81	-7.55
no apprenticeship	-48.51			
academics	89.54	total education effect	-0.61	-5.37
Table 4, regression (4)				
reference: with apprenticeship and 50-64 years		overall	-3.25	-27.39
youth	-27.07			
25-39	-26.26			
40-49	1.52	total age effect	-1.52	-12.97
no apprenticeship	-48.51			
academics	89.54	total education effect	-1.73	-14.42

Notes: Overall change is calculated as $((x_{t+15} - x_t)/x_t) * 100$. Long-run effects cumulate feedback over the period considered. Period: monthly data for January 1999 to December 2014; balanced county-level panel; observations: 76,782.

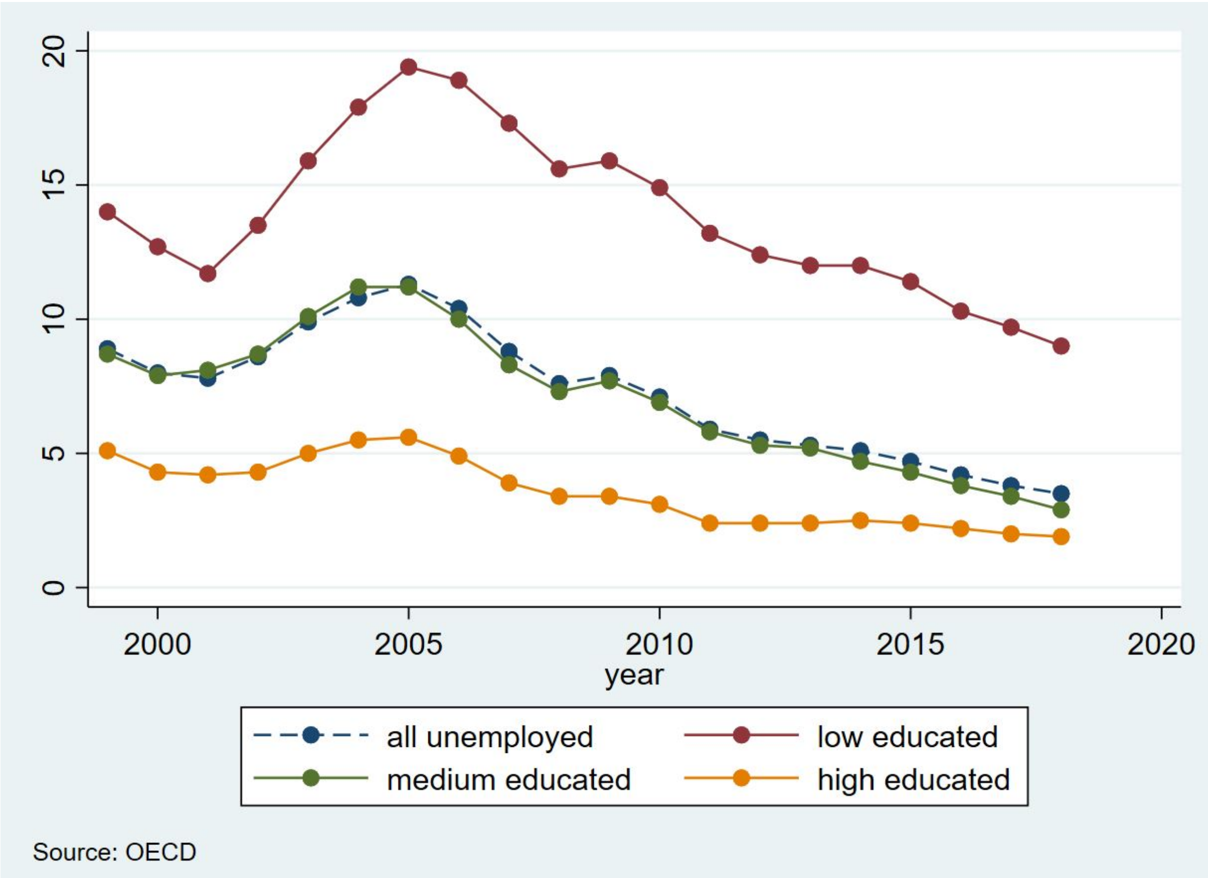

Figure 3: Unemployment Rates by Education Groups in Germany

Table 8: Further Results using Age, Education or Schooling

	age			apprentice-	secondary
reference group:	40-64	50-64	50-64	ship	education
considered groups:	(1)	(2)	(3)	(4)	(5)
log youth	0.041‡	0.039‡	0.038‡		
	(0.003)	(0.003)	(0.003)		
W(log youth)	0.001	0.001	-0.006		
	(0.006)	(0.005)	(0.006)		
log 25-39	0.016		0.013		
	(0.010)		(0.010)		
W(log 25-39)	0.034		0.053		
	(0.020)		(0.021)		
log 25-49		0.023			
		(0.018)			
W(log 25-49)		0.192‡			
		(0.034)			
log 40-49			0.004		
			(0.011)		
W(log 40-49)			0.083‡		
			(0.019)		
log no apprenticeship				0.082‡	
				(0.005)	
W(log no apprenticeship)				-0.022	
				(0.008)	
log academics				-0.006	
				(0.006)	
W(log academics)				0.059‡	
				(0.009)	
log no graduation					0.001
					(0.001)
W(log no graduation)					0.001
					(0.001)
log high school					-0.012
					(0.006)
W(log high school)					0.069‡
					(0.009)
spatial lag (λ)	0.241‡	0.239‡	0.239‡	0.240‡	0.238‡
time lag (γ)	0.809‡	0.807‡	0.807‡	0.799‡	0.811‡
spatial-time lag (π)	-0.116‡	-0.120‡	-0.121‡	-0.116‡	-0.119‡
within R^2	0.919	0.919	0.919	0.905	0.894

Notes: Dependent variable: log of unemployment rate; spatial lag, time lag, and spatial-time lag refer to the dependent; all regressions include fixed and time effects; county-cluster robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county level panel; †= FPR $\leq$0.05,‡= FPR $\leq$0.01.

Table 9: Short-Run and Long-Run Elasticities: Age and Schooling

	short-run elasticities			long-run elasticities		
considered groups:	direct	indirect	total	direct	indirect	total
dependent variable: log unemployment rate						
Table 5: Regression (2): reference: secondary education and 40-64 years						
youth	0.043	-0.008	0.035	0.234	0.157	0.391
	(0.003)	(0.008)	(0.009)	(0.020)	(0.149)	(0.161)
25-39	0.016	0.006	0.022	0.091	0.168	0.259
	(0.010)	(0.025)	(0.027)	(0.057)	(0.363)	(0.393)
no graduation	0.001	0.001	0.001	0.003	0.007	0.010
	(0.001)	(0.001)	(0.001)	(0.004)	(0.013)	(0.015)
high school	-0.011	0.076	0.065	-0.020	0.765	0.745
	(0.006)	(0.011)	(0.011)	(0.037)	(0.309)	(0.327)
Table 5: Regression (4): reference: secondary education and 50-64 years						
youth	0.040	-0.014	0.026	0.214	0.051	0.265
	(0.003)	(0.008)	(0.009)	(0.019)	(0.105)	(0.117)
25-39	0.018	0.035	0.053	0.115	0.429	0.544
	(0.010)	(0.027)	(0.028)	(0.059)	(0.323)	(0.351)
40-49	0.004	0.072	0.076	0.055	0.713	0.768
	(0.011)	(0.023)	(0.022)	(0.057)	(0.287)	(0.304)
no graduation	0.001	0.001	0.001	0.003	0.006	0.008
	(0.001)	(0.001)	(0.001)	(0.004)	(0.012)	(0.015)
high school	-0.016	0.060	0.044	-0.061	0.504	0.443
	(0.006)	(0.011)	(0.012)	(0.036)	(0.172)	(0.186)

Notes: Direct effects come from the local region, and the indirect effects come from the neighbouring regions. Long-run effects cumulate feedback over the period considered. Robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county-level panel; observations: 76,782.

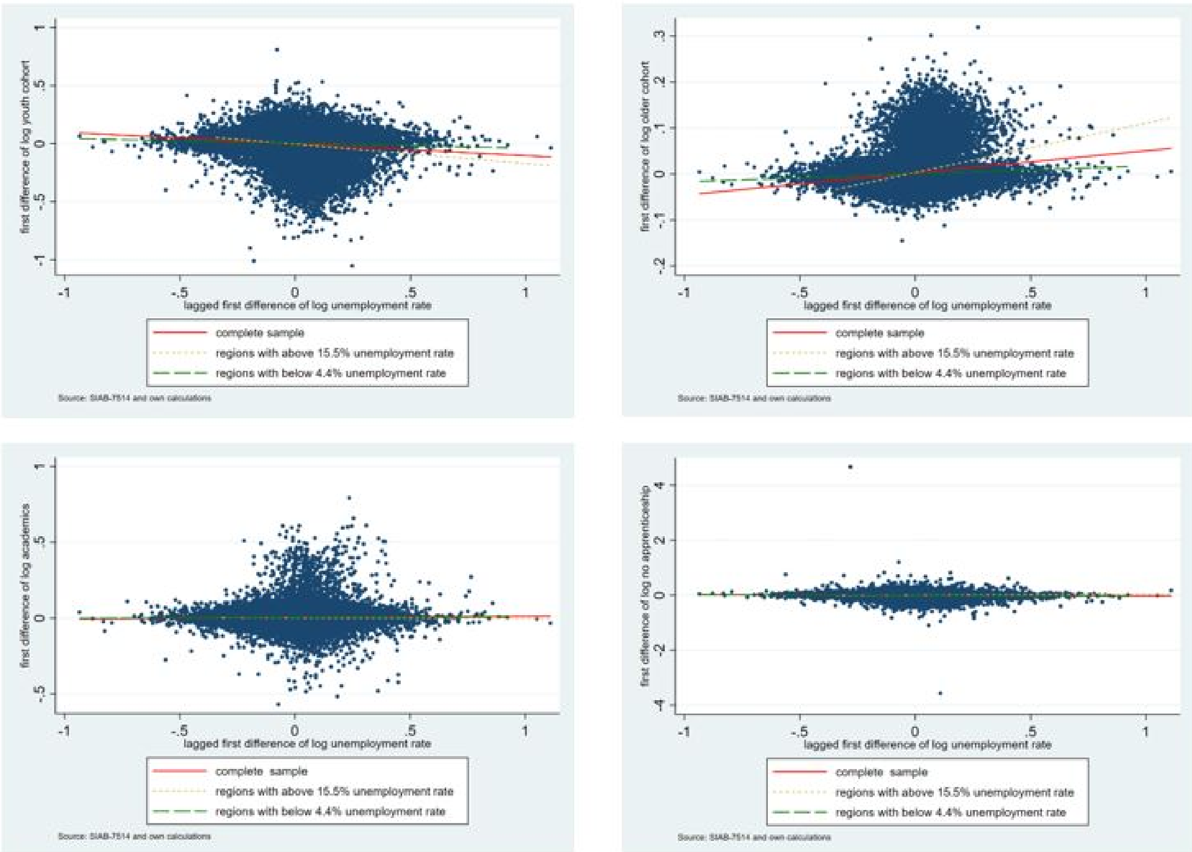

Figure 4: First Difference of Shares and Lagged First Difference of Unemployment Rate

Table 10: Results for Age and Education with Second Order Neighbourmatrix

	Dependent variable: log unemployment rate			
reference age group:	25-64	40-64	50-64	
considered groups:	(1)	(2)	(3)	(4)
log youth	0.026‡	0.025‡	0.024‡	0.024‡
	(0.003)	(0.003)	(0.003)	(0.003)
W(log youth)	-0.012	-0.011	-0.008	-0.012
	(0.009)	(0.011)	(0.010)	(0.011)
log 25-39		-0.007		-0.013
		(0.010)		(0.012)
W(log 25-39)		0.011		0.041
		(0.033)		(0.036)
log 25-49			-0.035	
			(0.020)	
W(log 25-49)			0.137	
			(0.053)	
log 40-49				-0.012
				(0.011)
W(log 40-49)				0.070
				(0.025)
log no apprenticeship	0.079‡	0.080‡	0.080‡	0.080‡
	(0.006)	(0.006)	(0.006)	(0.006)
W(log no apprenticeship)	-0.059‡	-0.060‡	-0.058‡	-0.058‡
	(0.010)	(0.010)	(0.010)	(0.010)
log academics	-0.013	-0.012	-0.011	-0.011
	(0.006)	(0.006)	(0.006)	(0.006)
W(log academics)	0.054‡	0.054‡	0.045†	0.040
	(0.014)	(0.014)	(0.014)	(0.015)
spatial lag (λ)	0.474‡	0.474‡	0.473‡	0.473‡
time lag (γ)	0.788‡	0.788‡	0.788‡	0.788‡
spatial-time lag (π)	-0.304‡	-0.304‡	-0.306‡	-0.307‡
within R^2	0.919	0.919	0.920	0.920
Observations	76,782	76,782	76,782	76,782

Notes: Spatial lag, time lag, and spatial-time lag refer to the dependent; all regressions include fixed and time effects; county-cluster robust standard errors are in parentheses; period: monthly data for January 1999 to December 2014; balanced county-level panel; †= FPR $\leq$ 0.05,‡= FPR $\leq$ 0.01.