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DISCUSSION PAPER SERIES

IZA DP No. 17715

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ABSTRACT

Rural Employment Evolutions*

A quarter of the population in high-income countries lives in rural areas. However, existing empirical evidence on these areas in OECD countries is scarce. Over the past several decades, many rural areas have been declining. Nevertheless, it is unclear whether these struggling rural areas are representative of the broad experience of the universe of rural areas. This paper provides a comprehensive analysis of employment evolutions for rural areas in Western Europe during the period 1970–2010. We first analyse 846 rural areas in France, Germany, Italy and the UK, and document large differences in overall employment growth across rural areas in all four countries. A sizable fraction of rural areas lost employment. However, employment in a significant number of rural areas grew during this period. The 90–10 percentile difference in decadal total employment growth of rural areas is 17.4 log points, representing an economically large difference. We then show, using data for Italy and the UK, that changes in the industry structure are fast in rural areas. The estimates also indicate that industry turnover is positively associated with employment growth. Moreover, the evidence shows that areas with stronger total employment growth exhibit stronger employment growth in the manufacturing of food and beverages. All conclusions are similar for rural remote areas. Taken together, our results lend support to the hypothesis that rural economies are not static entities; change is common in these areas, and employment evolutions often result from industry-level dynamics.

JEL Classification: R12, R32, J21, R11

Keywords: rural employment, spatial heterogeneity, industry turnover

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1 Introduction

A total of 25% of the population in OECD countries lives in rural areas (OECD, 2018). However, the urban and regional economics literature on high-income countries tends to focus mostly on cities.[1] In addition to a clear interest for regional economists, improved knowledge of the economics of rural areas is important in understanding the rise of the support for anti-system parties in many OECD countries (Algan et al., 2020; Bakker, 2021).

Over the past several decades, many rural areas have been declining in OECD countries. These developments have spurred a range of proposals for place-based policies to revitalize rural economies. EU member states carry out rural development programs (RDPs) at both national and regional levels. RDPs are financed jointly by the European Fund for Rural Development (EAFRD) and country budgets. The EAFRD budget for the 2014–2020 period was approximately 100 billion Euro (EU, 2017; ENRD, 2017; EU, 2021).[2] The UK is presently involved in a determined attempt to push in the same direction as part of its Levelling-up agenda (Swinney, 2021).

Nevertheless, it is unclear whether the struggling rural areas are representative of the broad experience of the universe of the rural areas in OECD countries. Research documenting the heterogeneity in employment growth across rural areas is limited. If there are indeed cases of strong employment growth, a relevant and understudied question is understanding the features of these rural areas.

In this paper, we study the employment evolutions of rural areas in Western Europe. First, we analyse 846 rural areas in France, Germany, Italy and the United Kingdom, providing a descriptive account of the differences in employment growth across rural areas between 1970 and the end of our sample period in 2010. Within each of the four countries, we find large geographic heterogeneity. Next, we document the degree of industry turnover. Finally, we seek to understand the features of rural areas with relatively high employment growth. Specifically, we focus on the relation between industry turnover and employment growth, and on changes in industries that are discussed in the policy debate on the economic development of rural areas. This analysis is performed using data from Italy and the UK since the industry classification is excessively broad in the earlier periods for France and Germany.

By studying the experiences of more than one country, we aim to make inferences that have a wider range of implications compared to those from one country. Although our specific estimates differ from one country to another, our findings are qualitatively consistent across the countries sampled. Despite the sizable differences across countries in policy, institutions and history, employment evolutions in rural areas in the sample countries appear to display—at least to some extent—shared economic influences.

[1] Although previous research provides some evidence on specific aspects of rural labour markets, such as rural–urban migration or the rural–urban wage gap, existing empirical evidence on employment evolutions in rural areas in high-income countries is scarce.

[2] Under the Common Agricultural Policy (CAP) transitional regulation (adopted on 23 December 2020), RDPs were extended for 2021 and 2022. During these years, RDPs were provided with 26.9 billion Euro from the EAFRD budget for 2021–27 and an extra 8.1 billion Euro from the next generation EU recovery instrument (EU, 2017).

We utilize a dataset created by merging and standardizing various country-speficic data sources for the four countries we are examining. Our analysis focuses on the Local Labor Market (LLM), which has slightly varied definitions in different countries, but we aimed to ensure it was as uniform as we could. The dataset comprises LLM-level observations formatted on a decadal basis. Armed with this dataset, we document several stylized facts at the LLM level. First, we document large differences in employment growth across space. In all countries, a sizable fraction of rural areas have lost employment. However, employment in a significant number of rural areas grew during this period. The 90–10 percentile difference in decadal total employment growth of rural areas is 17.4 log points, indicating an economically large difference and ranging from 9.9 log points in the UK to 18.1 log points in Italy. Conclusions are similar for rural remote areas.

Next, using data from Italy and the UK, we show that changes in industry structure are fast in rural areas, namely, there is considerable industrial turnover. Rural remote areas also experience a rapid change in the composition of their economic activity.

We then study whether industry turnover is positively associated with total employment growth. The evidence indicates that this is the case; a standard deviation increase in churning is associated with a 0.3 standard deviation increase in overall employment. Conclusions are again similar for rural remote areas.

Furthermore, we document the specific changes in the mix of local economic activity observed in rural areas featuring relatively high employment growth versus other areas. Specifically, we test whether the association between total employment growth and employment growth in a given industry is stronger for rural (low-density) versus intermediate-density LLMs. Note that we make this comparison because intermediate areas are more comparable to rural than urban areas. We repeat the same exercise for rural remote versus intermediate LLMs. As mentioned above, we focus on industries that are discussed in the policy debate. The estimates clearly indicate that rural areas exhibiting relatively high total employment growth experience stronger employment growth in the manufacturing of food and beverages. In particular, we find that for every 10 log points in total employment growth, rural areas experience a higher growth by 3.96 log-points in the manufacturing of food and beverages. The conclusions are similar for rural remote areas. The evidence also suggests that rural areas and rural remote areas with relatively high total employment growth experience stronger employment growth in hospitality. However, the estimate for rural areas is not very precise.

Taken together, our results support the hypothesis that rural economies are not static entities; change is common in these areas and, as in Duranton (2007), employment evolutions often result from industry-level dynamics.

Our paper adds to previous research in two ways. First, it adds to the literature on industry turnover and local evolutions, which generally focuses on cities. In particular, Duranton (2007) and Findeisen & Südekum (2008) stress fast changes in urban industry structures. [3] This literature includes Gagliardi et al. (2023), who investigate the consequences of the decline of

[3] See also Eaton & Eckstein (1997), Coulson (1999) and Black & Henderson (2003). Rosenthal & Ross (2015) provides a comprehensive review.

manufacturing in cities. Much of our analysis combines insights and approaches from Duranton (2007) and Gagliardi et al. (2023). Specifically, we use an overall conceptual framework similar to that used by Duranton (2007), and a closely related empirical approach when identifying industry turnover in rural areas. When documenting differences across rural areas in employment growth, our analysis is similar to Gagliardi et al. (2023).

Compared to this first body of literature, we focus more specifically on the analysis of rural areas, using a broad dataset in terms of geography. We carry out an analysis of employment evolutions in rural areas, documenting empirical regularities across the four Western European countries with the largest population.

Second, this paper adds to a thus far underdeveloped body of research on rural areas, and in particular, on rural labour markets.[4] A first strand studies the causes and consequences of migration from rural to urban areas—see Michaels et al. (2012) for evidence on the United States.[5] A second strand investigates policy programs that target (disadvantaged) rural areas. Recent evaluations of rural development programs include Behaghel et al. (2015), who analyse a tax-credit program in rural France, and Couture et al. (2021) who examine an e-commerce expansion in rural China.[6] Some previous research outside these two main strands investigates entrepreneurship in urban and rural labour markets (Faggio & Silva (2014) on UK data) and the labour market within rural regions (e.g., Baysan et al. (2024) study the allocation of labour between farm and non-farm employment in India).[7] Our paper is also related to Eckert & Peters (2022) and Eckert et al. (2023). The former shows that during the period 1880–1920 rural America was spared from the negative effects of agricultural decline thanks to technological catch-up. The latter paper reports that the emergence of "factory towns" in rural America played a crucial role in the industrialization of the United States.

Compared to this second body of literature, we concentrate on rural areas in OECD countries and recent decades, taking a longer-run approach and documenting changes at the LLM level. In essence, our study combines insights and methods from the literature on urban evolutions with a focus on rural employment.

The remainder of this paper is structured as follows. Section 2 describes the data. Section 3 provides the evidence based on the data analysis. Section 4 concludes the paper.

[4] See Kilkenny (2010) for a survey.

[5] See also Kim & Margo (2004), and recent surveys by Taylor & Martin (2001), Brueckner & Lall (2015) and Desmet & Henderson (2015).

[6] See also Canzian et al. (2019) and Asher & Novosad (2020). A review of earlier work in this area is provided by De Janvry et al. (2002). See Kline & Moretti (2014) and Neumark & Simpson (2015) for general surveys of place-based policies.

[7] See also Fafchamps & Quisumbing (1999), Lanjouw & Lanjouw (2001), Reardon et al. (2007). Bollman & Bryden (2000), Terluin & Post (2000), Terluin (2003) discuss the decline of agriculture and the rise in (tourism-related) services across OECD/EU predominantly rural regions and the differences in employment-growth paths during the 1980s and 1990s.

2 Data

We combine decadal census and survey data for France, Germany, Italy and the UK between the early 1970s and the early 2010s. We approximate the start-of-decade employment using the closest available year. For example, we use the Italian census of 2011 to approximate the employment at the start of the 2010s.

Our unit of analysis is the local labour market (LLM), defined as an area where most of the residents both live and work. For France and Italy, LLMs are territorial groupings of municipalities characterized by a certain degree of working-day commuting by the resident population. For Germany, they are groupings of districts, and for the UK, they are wards or postcode sectors.

More specifically, the analysis in this paper is based on decadal employment data for French *Zones d'Emploi*, German *Arbeitsmarktregionen*, Italian *Sistemi Locali del Lavoro* and British *Travel-to-Work Areas*.[8] Our data has a limitation in that we only possess similar data at the LLM level for the area of the former East Germany starting from 1990. Our focus is on LLMs within West Germany, which we will simply refer to as Germany throughout the paper.

For France, Italy and the UK we use census data.[9] The only German population census conducted between 1970 and the early 2010s was carried out in 1987, due to protests motivated by data-privacy concerns. We thus use employment statistics provided by the German Federal Statistical Office ("Erwerbstätigenrechnung") to measure employment for German LLMs in 1980, 1990, 2000 and 2010.[10] We complement this panel with LLM-specific decadal 2-digit industry-employment data from the Italian business census and the British Business Register and Employment Survey (BRES).

To identify rural LLMs, we build on a widely used OECD typology (OECD, 1994) that distinguishes between rural, intermediate and urban LLMs, based on the following two-step procedure. In the first step, each municipality of a LLM is defined as rural if its population density falls below 150 inhabitants per square kilometer. In the second step, LLMs are divided into rural, intermediate and urban LLMs, depending on the share of their population living in rural municipalities. In particular, an LLM is classified as rural if the share of its population living in rural municipalities exceeds 50%. Conversely, an LLM is classified as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200,000 and 500,000 inhabitants that represents at least 25% of the LLM population. Finally, an LLM is classified as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500,000

[8] For each country, we draw on the earliest available LLM classification, namely, on 1994 *Zones d'Emploi* (INSEE, 1987; Ronsac, 1994), 1990 *Arbeitsmarktregionen* (Eckey et al., 1990), 1981 *Sistemi Locali del Lavoro* (Sforzi, 1997) and 1984 *Travel-to-Work Areas* (Department of Employment, 1984; Coombes et al., 1986).

[9] Our census data also contains several LLM- and decade-specific sociodemographic variables such as female employment and population in three education (low, middle and high educated) and four age groups (0–24, 25–44, 45–64 and 65+).

[10] Similar to Pischke & Velling (1997), sociodemographic variables for German LLMs in 1980, 1990, 2000 and 2010 are drawn from databases of the Federal and State Statistical Offices as well as from the Federal Office for Building and Regional Planning.

inhabitants that represents at least 25% of the LLM population. We apply this classification in 1970 (the base period of our data panel) and use the resulting categorization for all subsequent decades.

In addition to population density, another important characteristic of LLMs related to their rurality is the distance to urban centers.[11] To capture this dimension, we rely on a second OECD typology that classifies geographies into remote and non-remote areas (Dijkstra & Poelman, 2008; Brezzi et al., 2011). Specifically, we categorize an LLM as remote if 50% of its inhabitants or more live in remote municipalities, that is, municipalities that exhibit driving distances to the nearest urban center (a municipality with 50,000 inhabitants or more) of more than 60 minutes. As with the degree of rurality detailed above, we apply this definition only to base periods, leaving it unchanged for all subsequent decades.

Table A.1 displays the resulting number of LLMs by degree of rurality and remoteness for the four countries in the data. The data feature 846 rural areas, of which 187 are remote. Appendix A.2 depicts country-specific maps of all LLMs listed in Table A.1. Table A.2 presents summary statistics in 1970 and 2010—the beginning and end of our period of analysis—for the full sample. Appendix A.3 presents the same summary statistics by country. Appendix B provides a detailed description of the dataset.

3 Evidence

3.1 Differences Across Rural Areas in Employment Growth

In this Section we provide a descriptive account of geographical heterogeneity in employment changes across rural and rural remote areas during the period 1970–2010. Our analysis echoes that of Gagliardi et al. (2023), who document significant heterogeneity in employment growth across cities after the start of a manufacturing decline at the country level.

Figure 1 displays kernel density estimates for the employment-growth distribution of rural and rural remote areas. We present both estimates when all countries are pooled together and the corresponding distributions by country. Visual inspection of Figure 1 indicates that there are large differences in employment growth across rural and rural remote areas within each country. Rural areas to the left of 0 experienced employment declines in the period after 1970, while rural areas to the right of 0 experienced employment gains during the same period. In every country, a large portion of the distribution lies to the left of 0, as a significant number of rural areas have experienced job losses. Nevertheless, a noteworthy segment of the distribution is above 0, showing that employment increased in many rural areas during this time. Table 1 substantiates these claims by presenting the standard deviation of employment growth and the differences between the 90th and 10th percentile (p90–p10) for the whole dataset and by country. Note that it is not possible to report this output for rural remote areas in Germany

[11] The economic significance of this dimension is, for example, stressed by Redding & Sturm (2008), who use the fall of the Iron Curtain to study the consequences of remoteness and a lack of market access as well as by the literature on transport-network extensions surveyed in Redding & Turner (2015).

due to the sample size.

For example, the 90–10 percentile difference in decadal total employment growth of rural areas is 17.4 log points. This represents an economically large difference that ranges from 9.9 log points in the UK to 18.1 log points in Italy, indicating vast differences in overall employment growth across rural communities within each country. All conclusions are similar when focusing on rural remote areas. For comparisons, Table A.3 reports the same statistics for urban and intermediate-density areas.

3.2 Degree of Industry Turnover

Section 3.1 reveals that there are vast differences in overall employment growth across rural communities within each country. In this Section, we seek to understand whether there is considerable industry turnover in rural areas. We use a conceptual framework and empirical approach similar to that used by Duranton (2007). Table 2 reports the industry-churning rate of LLMs, a structural-change measure based on industry-level employment. For each LLM, this measures averages decadal relative employment gains and losses over all industries and decades:[12]

$$Churn_l = \frac{1}{4 \cdot J} \sum_{t=1970}^{2000} \sum_{j=1}^{J} \frac{|e_{l,j,t+1} - e_{l,j,t}|}{e_{l,j,t}} \tag{1}$$

where j indexes industries ($J = 60$) and $e_{l,j,t}$ is the employment of LLM l in industry j and decade t.

The sample here consists of LLMs in Italy and the UK, the two countries for which the industry breakdown is feasible at the local level and with the data at our disposal. Table 2 also reports the aggregate total-employment change as:

$$\Delta EMP_l = \frac{1}{4} \sum_{t=1970}^{2000} \frac{|e_{l,t+1} - e_{l,t}|}{e_{l,t}} \tag{2}$$

Table 2 shows that on average across rural areas, the industry-churning rate is 6.8 times as large as the aggregate employment change. This indicates that the typical rural area saw its industries change by 6.8 times the amount necessary to accommodate aggregate employment changes. Table 2 also shows that the typical rural remote area saw its industries change by 5.8 times the amount necessary to accommodate aggregate employment changes. Therefore, changes in the industry structure are fast in rural areas. This finding is not driven by outliers: the results are qualitatively similar if we remove absolute employment growth rates above the 99th percentile by country.[13]

[12] See Davis & Haltiwanger (1998), Duranton (2007) and Findeisen & Südekum (2008) for examples of previous applications.

[13] Duranton (2007) and Findeisen & Südekum (2008) report yearly churning rates for US (1977–1997) and French (1985–1993) cities, and German (1977-2002) cities, respectively. Notice the following differences:

3.3 Industry Turnover and Employment Growth

What is the relation between industry turnover and employment growth? To explore this question, we regress the decadal log change in employment on the decadal industry churning rate:

$$\Delta y_{l,r,c,t} = \beta_c Churn_{l,t} + \lambda_t + \varphi_{r,t} + \pi \Delta X_{l,t} + \eta_{l,r,c,t} \quad (3)$$

where $\Delta y_{l,r,c,t}$ is the log change in total employment for LLM l in NUTS-1 region r, country c and decade t; $Churn_{l,t}$ is the decadal industry-churning rate;[14] λ_t are decade fixed effects; $\varphi_{r,t}$ are region $\times$ decade fixed effects; $\Delta X_{l,t}$ are changes in basic LLM characteristics; and $\eta_{l,r,c,t}$ is the error term. LLM-level controls include first-differences of population shares of three age groups (25–44, 45–64 and 65+) and employment shares of female and high-qualified workers. The conclusions are very similar if we do not include these controls, or if we include their initial levels instead of first differences. Note that this specification is similar to a four-period fixed-effects model and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side.[15] Our analysis echoes that in Findeisen & Südekum (2008) for German cities. To limit the impact of outliers, which are typically observed in very small LLMs, on the regression analysis, both the outcome variable, $\Delta y_{l,r,c,t}$, and the key explanatory variable, $Churn_{l,t}$, are winsorized at the 1st and 99th percentiles. The conclusions remain unchanged if we use unwinsorized data, or if the variables are winsorized at the 5th and 95th percentiles.

Table 3 summarizes the association between industry churning and employment growth. The estimates indicate that industry turnover is positively associated with employment growth. For rural areas, a standard deviation increase in churning (1.84) is associated with a 2.4 percent increase in employment (significant at the 1 percent level). This is equivalent to a 0.3 standard deviation increase (the standard deviation of total employment growth in this sample of rural LLMs, which belong to Italy and UK, is 0.073). For rural remote areas, a standard deviation increase in churning (1.013) is associated with a 2.3 percent increase in employment (significant at the 1 percent level). This is equivalent to a 0.29 standard deviation increase (the standard deviation of total employment growth in this sample of rural remote LLMs is 0.082).

3.4 Industry-level Dynamics in Areas with Relatively High Total Employment Growth

Sections 3.2 and 3.3 indicate that (a) there is considerable industry turnover in rural areas; and (b) industry turnover is positively associated with employment growth. In this Section we address the following question: Do rural areas with relatively high total employment growth feature stronger employment growth in certain industries? To investigate this issue, we test

we focus on rural areas; we report decadal instead of yearly churning rates; we analyze Italy and the UK; and we study a different period (1970–2010).

[14] $Churn_{l,t} = \frac{1}{J} \sum_{j=1}^{J} \frac{|e_{l,j,t} - e_{l,j,t-1}|}{e_{l,j,t-1}}$

[15] As pointed out by Autor et al. (2013), the stacked first-differenced version poses slightly less restrictive assumptions on the error term relative to a multiperiodic fixed-effects model.

whether the association between total employment growth and employment growth in a given industry is stronger for rural versus intermediate LLMs.[16] We make this comparison as intermediate areas are more comparable to rural than urban areas (e.g., Table A.3 and Table 1). As mentioned above, we focus on industries that are discussed in the policy debate on the economic development of rural areas: food and beverages manufacturing, hospitality, culture and retail trade, respectively (Table A.4 presents summary statistics for these four variables). *Food and beverages manufacturing* is commonly discussed in this debate; *hospitality* is also often discussed, particularly in relation to *gastronomy and wine tourism*. See EU (2017), ENRD (2017) and UN-Tourism (2023) for examples of discussions. Culture and retail trade are also sometimes discussed (due to their link to the hospitality industry), albeit indirectly (UNESCO, 2020; Eurostat, 2021).[17]

We estimate the following equation on the sample of LLMs classified as rural or intermediate:

$$\Delta e_{l,r,c,t} = \beta_y \Delta y_{l,r,c,t} + \theta \; rural_l \times \Delta y_{l,r,c,t} + \lambda_t + \varphi_{r,t} + \pi \Delta X_{l,t} + \nu_{l,r,c,t} \tag{4}$$

where $\Delta e_{l,r,c,t}$ are log changes[18] in industry-level employment in (a) food and beverages manufacturing, (b) hospitality, (c) culture or (d) retail trade. $\Delta y_{l,r,c,t}$ are log changes in *total* employment for LLM l in NUTS-1 region r, country c, and decade t. As above, λ_t are decade fixed effects, $\varphi_{r,t}$ are region $\times$ decade fixed effects, $\Delta X_{l,t}$ are changes in basic LLM characteristics, and $\nu_{l,r,c,t}$ is the error term. LLM-level controls include first-differences of population shares of three age groups (25–44, 45–64 and 65+) and employment shares of female and high-qualified workers. The conclusions are very similar if we do not include these controls, or if we include their initial levels instead of first differences. Note that the model is estimated in stacked first differences and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side—these include $rural_l$. We repeat the same exercise for rural remote versus intermediate LLMs. The estimation sample consists of LLMs in Italy and the UK, the two countries for which the industry breakdown is feasible at the local level and with the data at our disposal. To limit the impact of outliers, which are typically observed in very small LLMs, on the regression analysis, both the outcome variables, $\Delta e_{l,r,c,t}$, and the key right-hand-side variable, $\Delta y_{l,r,c,t}$, are winsorized at the 1st and 99th percentiles. The conclusions remain unchanged if we use unwinsorized data, or if the variables are winsorized at the 5th and 95th percentiles.

Table 4 presents the results. In Column 1, the estimates clearly indicate that growth variation in total employment is positively and significantly associated with growth variation in the manufacturing of food and beverages. In particular, we find that for each 10 log-points in total employment growth, rural areas experience a higher growth by 3.96 log-points in the

[16] This approach is similar in spirit to the analysis of minimum wage effects in Card (1992).

[17] Quoting from UNESCO (2020): 'Tourism can provide direct jobs to the community, such as tour guides or in the hospitality industry (hotels, bars and restaurants). Indirect employment is generated through other industries such as agriculture, food production, creative industries (art and music performance), and retail (souvenirs).'

[18] The main conclusions from the below analysis are unchanged if we use the inverse hyperbolic sine transformation instead of the log transformation

manufacturing of food and beverages. The conclusions are qualitatively similar for rural remote areas: we find that for each 10 log-points in total employment growth, they experience a higher growth by 5.69 log-points in the manufacturing of food and beverages. In Column 2, the estimates suggest that growth variation in total employment is positively and significantly associated with growth variation in hospitality: for each 10 log-points in total employment growth, rural areas experience a higher growth by 1.08 log-points in hospitality. The conclusions are again qualitatively similar for rural remote areas: for each 10 log-points in total employment growth, rural areas experience a higher growth by 2.44 log-points in hospitality. We caution, neverthless, that the coefficient estimate for rural areas lacks precision. In Columns 3 (culture) and 4 (retail trade) we cannot reject the null hypothesis of no relation between total employment and industry growth, neither for rural areas nor rural remote areas.

4 Conclusions

A quarter of the population in high-income countries lives in rural areas. However, the urban and regional economics literature on high-income countries tends to focus mostly on cities. This paper analyses employment evolutions in rural areas in Western Europe. We address the following questions. Are there large differences across rural areas in employment growth? Is there considerable industry turnover in rural areas? Is the industry turnover positively associated with employment growth? What specific changes in the mix of local economic activity do we observe in rural areas featuring relatively high employment growth?

We document large differences in employment growth across rural areas. The evidence also indicates that there is considerable industry turnover in rural areas. Moreover, the estimates indicate that industry turnover is positively associated with employment growth. Finally, the evidence clearly indicates that rural and rural remote areas featuring relatively high total employment growth experience stronger employment growth in the manufacturing of food and beverages. Overall, our evidence lends support to the hypothesis that rural economies are not static entities; change is common in these areas and employment evolutions often result from industry-level dynamics.

The channels by which industry-level dynamics drive employment evolutions at a more micro level remain to be determined. First, innovation-driven shocks may propel the churning of industries across rural areas. Employment in rural areas then increases or decreases as a result of expansions or declines at the industry level (Duranton, 2007). Second, the movements of a very small number of firms may explain an important part of the variation in the observed employment growth across rural areas (Gabaix, 2011; Shinnosuke & O'Connor, 2024). These channels are not mutually exclusive. Understanding their relative role is an important task for future work.

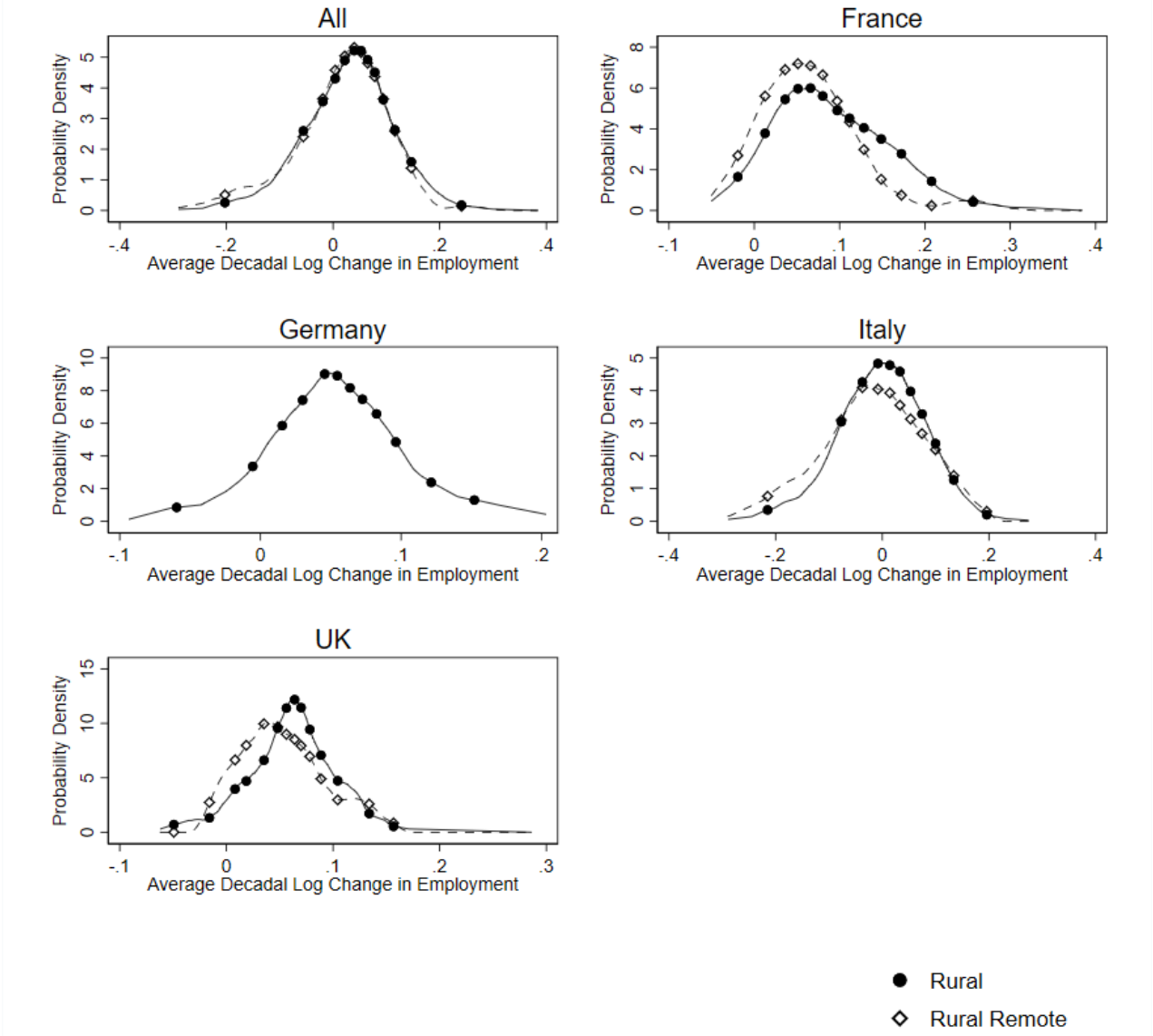

FIGURE 1: SPATIAL DISTRIBUTION OF EMPLOYMENT GROWTH IN RURAL AND REMOTE AREAS.

Notes: Kernel density estimates of mean decadal log changes in total employment between 1970 and 2010 for rural and rural remote LLMs. For Germany, it is not possible to report the distribution for rural remote areas due to the sample size (see Table A.1). Germany includes only LLMs in West Germany.

Table 1: Geographical Variation in Employment Growth

	Rural	Rural Remote
A. Whole Sample		
Std. Deviation	0.0721	0.0682
p90-p10	0.1736	0.1405
B. France		
Std. Deviation	0.0626	0.0490
p90-p10	0.1603	0.1017
C. Germany		
Std. Deviation	0.0498	–
p90-p10	0.1158	–
D. Italy		
Std. Deviation	0.0747	0.0869
p90-p10	0.1814	0.2416
E. UK		
Std. Deviation	0.0392	0.0365
p90-p10	0.0986	0.1022

Notes: Entries are summary statistics for the distribution of average decadal log changes in total employment between 1970 and 2010 in rural and rural remote areas. All statistics are weighted by population shares of LLMs in base period (1970). For Germany it is not possible to report these statistics for rural remote areas because of sample size - See Table A.1. Germany includes only Local Labor Markets in West Germany.

Table 2: Churning

	Rural	Rural Remote
Industry Churning	1.3264 (1.8401)	1.2116 (1.0129)
Aggregate Employment Change	0.1962 (0.2097)	0.2087 (0.2272)
LLMs	596	128

Notes: The Table describes industry movements across rural and rural remote areas. Entries show industry churning indices as well as aggregate percentage changes in total employment by LLM type. Standard deviations in parentheses. All statistics are weighted by population shares of LLMs in base periods (1970). Calculations are based on LLM-specific NACE Rev. 1 2-digit industry-employment data for Italy and the UK.

Table 3: Association between Industry Churning and Employment Growth by LLM Type.

	Dependent Variable: Decadal Δ Log Employment	
	(1) Rural	(2) Rural Remote
Industry-Churning Rate	0.0128***	0.0231***
	(0.0030)	(0.0048)
Decade FE	Yes	Yes
Region × Decade FE	Yes	Yes
LLMs	596	128
N	2384	512

Notes: Results are coefficients and standard errors from regressions of decadal LLM-specific log changes in total employment on decadal LLM-specific industry-churning rates. All regressions are weighted by population shares of LLMs in base periods (1970). Standard errors are clustered by NUTS-2 regions. Industry-churning rates are calculated from LLM-specific NACE Rev. 1 2-digit industry-employment data for Italy and the UK. LLM-level controls include first-differences of population shares of three age groups (25-44, 45-64, 65+), employment shares of female and high-qualified workers. Conclusions are very similar if we do not include these controls or we include their initial levels instead of first-differences. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Overall Employment Growth and Industry-level Growth

	(1) Δ Food and Beverages	(2) Δ Hospitality	(3) Δ Culture	(4) Δ Retail
A. Rural versus Intermediate LLMs				
Δ Employment × Rural	0.3956**	0.1079*	-0.0533	-0.0405
	(0.1816)	(0.0629)	(0.1519)	(0.0595)
LLMs	944	944	934	944
B. Rural remote versus Intermediate LLMs				
Δ Employment × Rural remote	0.5686**	0.2444**	-0.5208	-0.0434
	(0.2498)	(0.1022)	(0.3267)	(0.1183)
LLMs	476	476	471	476

Notes: Rows show coefficients and standard errors from *separate* regressions of LLM-specific decadal log changes in industry-employment on decadal log changes in total employment, and interaction with dummies indicating rural (panel A) or rural remote LLMs (panel B). All regressions are weighted by population shares of LLMs in base periods (1970). Decade FE and Region × Decade FE always included. See Equation 4. Note that the model is estimated in stacked first differences and thus differences out any unobservable time-invariant LLM-specific confounders on the right-hand side - these include dummies indicating rural or rural remote LLMs. Standard errors are clustered by NUTS-2 regions. LLM-level controls include first-differences of population shares of three age groups (25-44, 45-64, 65+), employment shares of female and high-qualified workers. Conclusions are very similar if we do not include these controls or we include their initial levels instead of first-differences. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

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A Online Appendixes

A.1 Main Summary Statistics

Table A.1: Total Number of LLMs by Degree of Rurality and Remoteness.

	Urban		Intermediate		Rural	
	Non-Remote	Remote	Non-Remote	Remote	Non-Remote	Remote
France	30	0	110	7	143	58
Germany	34	0	74	1	48	1
Italy	198	4	210	13	425	105
UK	115	3	109	16	43	23
Total	377	7	503	37	659	187

Notes: Germany includes only Local Labor Markets in West Germany.

Table A.2: Characteristics of Urban, Intermediate and Rural LLMs, 2010 versus 1970.

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	55.69	53.86	29.06	31.13	15.24	15.01	2.60	2.43
% of Sample Employment	59.22	56.28	27.73	30.38	13.05	13.34	2.00	1.93
B. Total Size (Average LLM, 1,000 individuals)								
Population	1346.18 (1501.88)	1435.78 (1686.53)	261.51 (242.63)	330.57 (305.66)	82.98 (61.37)	102.72 (74.93)	62.41 (43.64)	73.62 (52.08)
Employment	588.01 (766.54)	670.07 (841.84)	97.51 (105.66)	140.10 (148.02)	27.69 (25.22)	39.65 (34.25)	16.74 (10.65)	23.07 (15.20)
C. Sectoral Structure (Average LLM, %)								
Agriculture	4.25 (6.75)	1.55 (2.78)	12.98 (8.48)	3.26 (3.04)	27.61 (12.09)	6.95 (5.30)	28.81 (12.34)	7.71 (5.83)
Manufact.	46.20 (10.63)	20.75 (7.53)	42.52 (10.27)	24.22 (7.10)	36.77 (10.39)	26.86 (7.55)	32.25 (10.40)	23.95 (7.02)
Services	49.54 (11.48)	77.70 (8.47)	44.51 (10.63)	72.52 (7.86)	35.62 (9.58)	66.20 (7.89)	38.94 (11.00)	68.34 (7.76)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	40.84 (8.27)	44.04 (8.05)	36.65 (9.22)	41.13 (8.50)	32.90 (8.85)	37.47 (8.13)	29.63 (8.06)	33.44 (6.81)
% Female Employment	32.16 (5.39)	45.42 (3.53)	31.44 (5.46)	45.59 (3.46)	30.89 (6.73)	44.42 (4.21)	30.01 (5.30)	45.79 (4.26)
% High Qual. Workforce	5.92 (3.47)	25.17 (13.18)	4.95 (3.09)	22.87 (12.78)	3.31 (2.00)	19.00 (10.34)	4.13 (2.41)	23.23 (8.54)
% Aged 65+	12.06 (2.50)	17.89 (3.60)	12.80 (2.62)	19.05 (3.19)	14.14 (2.90)	20.76 (3.28)	15.73 (3.03)	22.76 (2.96)
LLMs	384	384	540	540	846	846	187	187

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

Table A.3: Geographical Variation in Employment Growth in Urban and Intermediate Areas

	Urban	Intermediate
A. Whole Sample		
Std. Deviation	0.0460	0.0566
p90-p10	0.1287	0.1375
B. France		
Std. Deviation	0.0408	0.0617
p90-p10	0.1102	0.1793
C. Germany		
Std. Deviation	0.0380	0.0396
p90-p10	0.0956	0.1022
D. Italy		
Std. Deviation	0.0498	0.0528
p90-p10	0.1384	0.1413
E. UK		
Std. Deviation	0.0359	0.0397
p90-p10	0.0946	0.0843

Notes: Entries are summary statistics for the distribution of average decadal log changes in total employment between 1970 and 2010 in urban and intermediate areas. All statistics are weighted by population shares of LLMs in base period (1970). For Germany it is not possible to report these statistics for rural remote areas because of sample size - See Table A.1. Germany includes only Local Labor Markets in West Germany.

Table A.4: summary statistics for the growth rates of industry-level employment

	Mean	SD	p90-p10
A. Rural			
Δ Food and Beverages	0.0730	0.1853	0.4448
Δ Hospitality	0.2439	0.1128	0.2724
Δ Culture	0.3165	0.2872	0.5921
Δ Retail	0.0501	0.1643	0.4675
B. Rural Remote			
Δ Food and Beverages	0.0837	0.2076	0.5138
Δ Hospitality	0.2446	0.1317	0.3372
Δ Culture	0.3585	0.3085	0.7002
Δ Retail	0.0812	0.1843	0.4821

Notes: The table shows summary statistics for decadal log changes in sector- or industry-employment for rural (panel A) and rural remote (panel B) LLMs. All statistics are weighted by population shares of LLMs in base period (1970).

A.2 Geographic Distribution of Rural, Intermediate, Urban and Remote Local Labour Markets

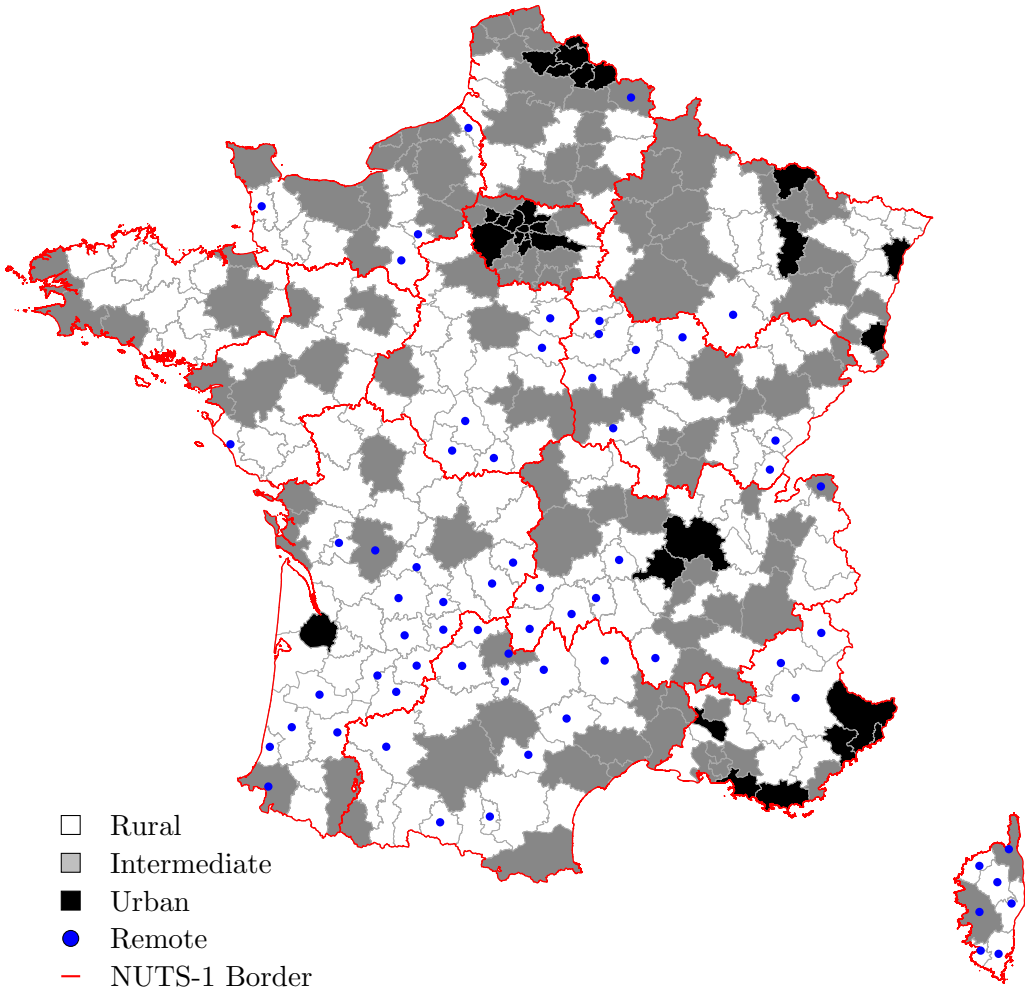

FIGURE A.1: RURAL, INTERMEDIATE AND URBAN LOCAL LABOUR MARKETS IN FRANCE.

Notes: Figure shows 1994 French LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra & Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region.

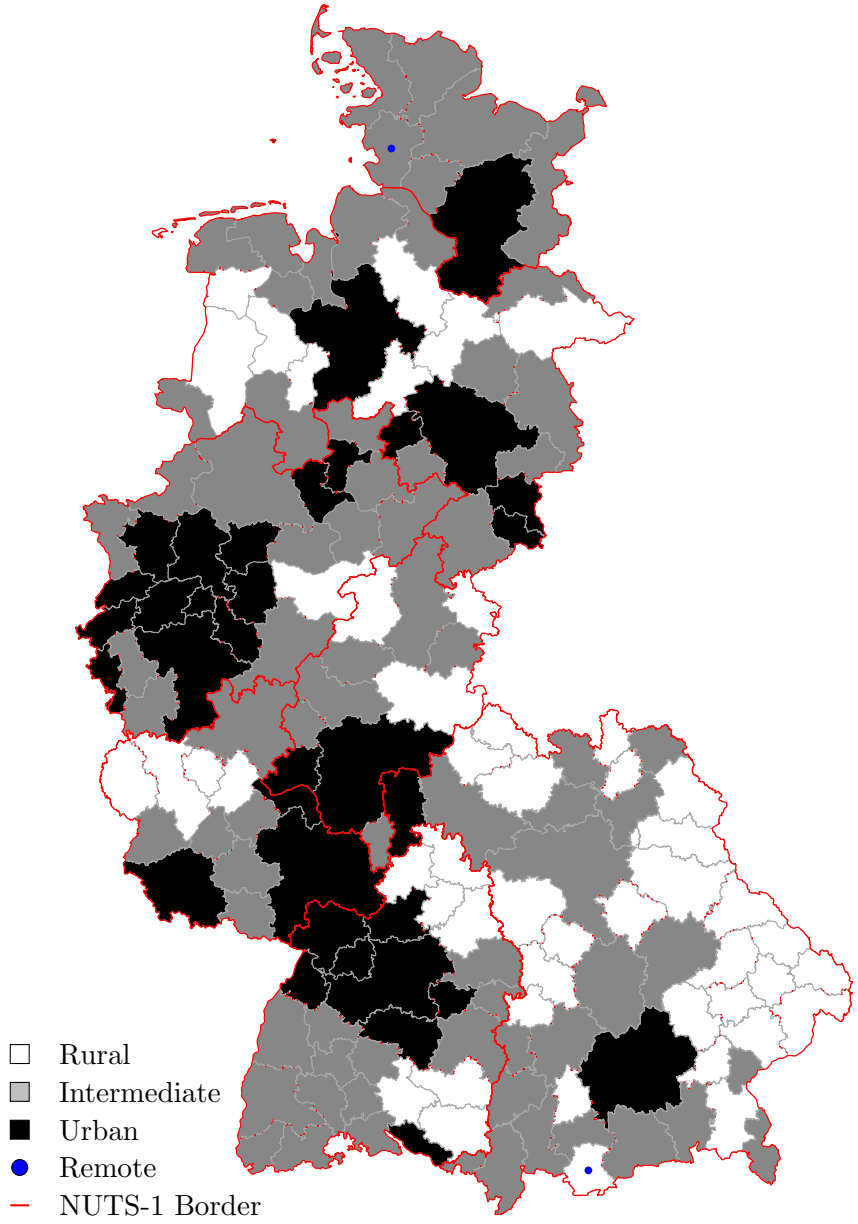

FIGURE A.2: RURAL, INTERMEDIATE AND URBAN LOCAL LABOUR MARKETS IN GERMANY.

Notes: Figure shows 1990 German LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra & Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region. The city states of Bremen and Hamburg are (respectively) merged with the territorial states of Niedersachsen and Schleswig-Holstein. Moreover, the small territorial state of Saarland is merged with the neighboring states of Rhineland Palatinate.

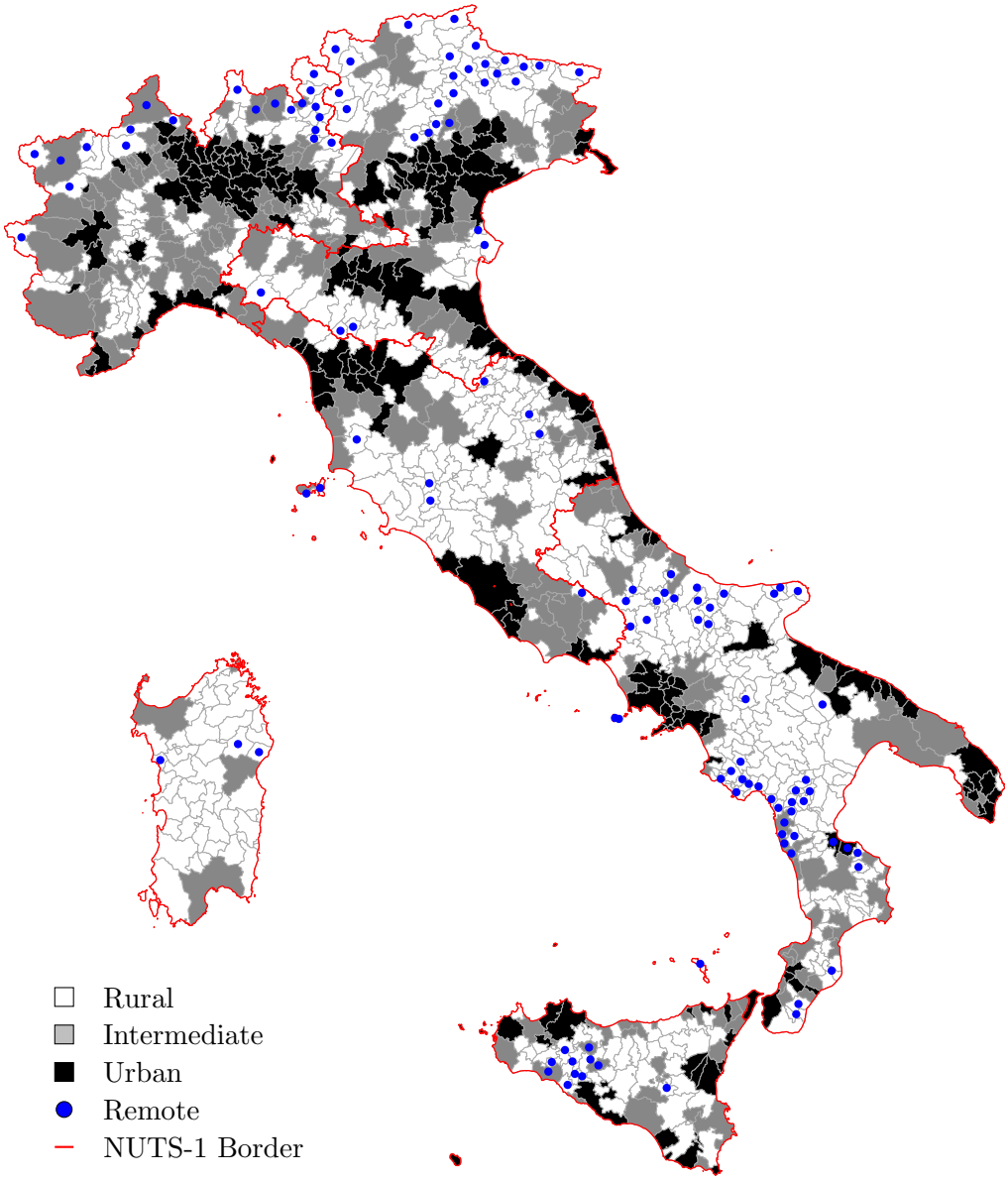

FIGURE A.3: RURAL, INTERMEDIATE AND URBAN LOCAL LABOUR MARKETS IN ITALY.

Notes: Figure shows 1981 Italia LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra & Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region. Sardinia and Sicily together form one NUTS-1 region.

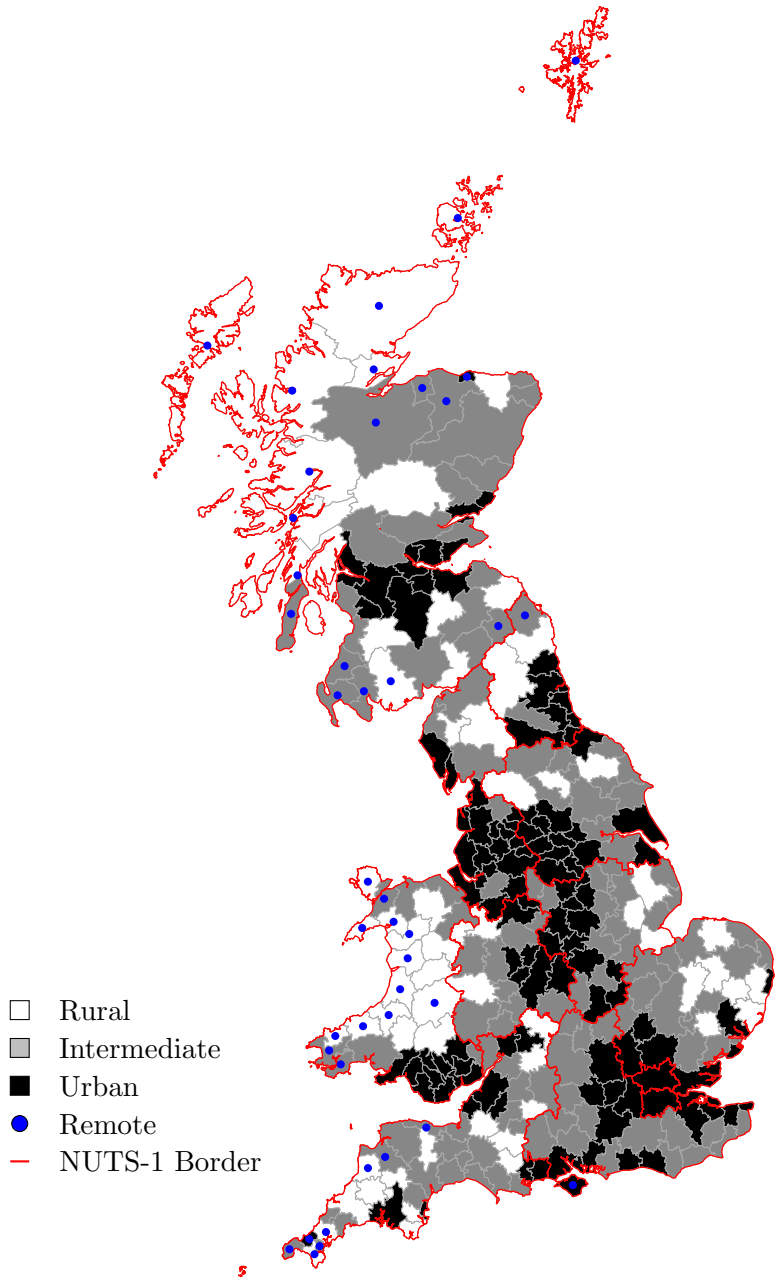

FIGURE A.4: RURAL, INTERMEDIATE AND URBAN LOCAL LABOUR MARKETS IN THE UK.

Notes: Figure shows 1984 British LLMs by degree of rurality and remoteness. Rural and remote LLMs are classified based on OECD (1994); Dijkstra & Poelman (2008); Brezzi et al. (2011). NUTS-1 borders are borders around those LLMs the centroid of which lies in the same NUTS-1 region.

A.3 Country-Specific Summary Statistics

A.3.1 France

Table A.5: Characteristics of French Urban, Intermediate and Rural LLMs, 2010 versus 1970.

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% Sample Population	33.62	31.90	38.16	40.80	28.22	27.30	7.09	6.34
% Sample Employment	36.54	32.88	36.69	40.39	26.77	26.74	6.69	5.90
B. Total Size (Average LLM, 1,000 individuals)								
Population	996.22 (720.69)	1077.87 (656.01)	253.90 (165.24)	367.54 (285.73)	90.64 (39.96)	115.94 (60.30)	84.30 (38.19)	97.49 (47.07)
Employment	298.91 (238.01)	366.72 (245.90)	64.44 (43.54)	118.91 (99.37)	22.63 (10.32)	36.73 (20.77)	20.95 (9.71)	29.09 (14.10)
C. Sectoral Structure (Average LLM, %)								
Agriculture	1.84 (1.92)	0.42 (0.44)	12.02 (6.05)	2.42 (1.78)	26.91 (10.73)	5.75 (3.20)	28.48 (9.71)	6.86 (3.18)
Manufact.	41.75 (9.68)	15.80 (4.72)	40.44 (9.40)	21.68 (4.59)	34.61 (10.02)	25.39 (5.79)	31.61 (9.17)	23.77 (5.42)
Services	56.40 (10.19)	83.78 (4.98)	47.54 (7.70)	75.91 (5.14)	38.49 (7.41)	68.86 (6.17)	39.91 (7.11)	69.37 (5.69)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	28.47 (4.00)	32.94 (3.14)	25.19 (2.04)	31.64 (2.43)	24.85 (1.84)	31.29 (2.66)	24.73 (1.51)	29.77 (1.82)
% Female Employment	34.19 (6.33)	48.53 (1.34)	30.90 (4.45)	47.76 (1.22)	31.87 (4.12)	47.26 (1.14)	31.47 (3.90)	47.62 (1.41)
% High Qual. Workforce	10.42 (4.34)	44.38 (11.89)	6.94 (2.54)	35.42 (7.41)	4.44 (1.25)	27.79 (4.56)	4.58 (1.19)	26.93 (3.97)
% Aged 65+	11.82 (2.96)	15.00 (2.92)	12.31 (2.32)	17.02 (3.22)	15.37 (2.65)	20.22 (3.56)	16.80 (2.26)	23.09 (2.55)
LLMs	30	30	117	117	201	201	58	58

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

A.3.2 Germany

Table A.6: Characteristics of German Urban, Intermediate and Rural LLMs, 2010 versus 1970.

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	55.09	53.88	33.94	34.90	10.97	11.22	0.13	0.13
% of Sample Employment	55.54	55.44	33.48	33.70	10.99	10.85	0.14	0.13
B. Total Size (Average LLM, 1,000 individuals)								
Population	1697.42 (879.20)	1865.28 (980.48)	423.35 (318.85)	494.98 (379.94)	155.91 (67.07)	178.14 (74.94)	75.42 (.)	86.31 (.)
Employment	749.25 (391.25)	985.33 (551.01)	182.72 (144.94)	247.54 (205.13)	67.62 (28.04)	87.13 (38.46)	35.47 (.)	41.28 (.)
C. Sectoral Structure (Average LLM, %)								
Agriculture	3.52 (2.14)	1.23 (0.52)	10.41 (3.79)	2.76 (1.09)	20.82 (6.27)	4.66 (1.41)	6.67 (.)	3.12 (.)
Manufact.	51.10 (7.26)	23.04 (6.29)	47.49 (8.56)	27.39 (6.86)	44.20 (7.45)	31.95 (6.38)	28.26 (.)	14.20 (.)
Services	45.38 (7.07)	75.73 (6.49)	42.10 (7.92)	69.84 (6.71)	34.97 (6.36)	63.38 (6.49)	65.07 (.)	82.69 (.)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	43.98 (3.72)	51.67 (5.56)	43.03 (3.23)	48.50 (4.25)	43.69 (2.64)	48.57 (4.54)	47.03 (.)	47.83 (.)
% Female Employment	34.45 (3.37)	44.76 (1.78)	35.77 (3.79)	45.04 (3.12)	38.23 (3.45)	43.89 (3.60)	41.11 (.)	54.51 (.)
% High Qual. Workforce	3.51 (1.02)	15.41 (4.05)	3.01 (0.71)	10.43 (2.44)	2.50 (0.41)	7.08 (1.46)	4.10 (.)	7.64 (.)
% Aged 65+	12.84 (1.43)	20.19 (1.23)	12.99 (1.50)	20.21 (1.57)	12.83 (1.48)	19.95 (1.93)	14.75 (.)	23.97 (.)
LLMs	34	34	75	75	49	49	1	1

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

A.3.3 Italy

Table A.7: Characteristics of Italian Urban, Intermediate and Rural LLMs, 2010 versus 1970.

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	56.39	57.11	24.74	25.59	18.88	17.30	2.61	2.22
% of Sample Employment	56.30	57.45	25.05	25.88	18.65	16.67	2.59	2.13
B. Total Size (Average LLM, 1,000 individuals)								
Population	903.85 (1004.12)	829.66 (964.74)	129.69 (114.59)	151.58 (134.34)	35.20 (30.82)	40.04 (35.92)	18.49 (13.27)	20.41 (17.88)
Employment	309.83 (350.55)	315.46 (373.49)	44.38 (37.19)	57.52 (46.09)	11.65 (9.46)	14.63 (12.78)	6.44 (5.05)	7.45 (6.31)
C. Sectoral Structure (Average LLM, %)								
Agriculture	10.05 (11.10)	4.08 (4.59)	21.65 (12.08)	6.74 (4.79)	34.02 (13.94)	11.00 (7.69)	33.12 (16.39)	11.35 (10.21)
Manufact.	45.90 (13.59)	25.25 (9.50)	43.25 (11.24)	28.14 (8.72)	36.96 (10.07)	27.33 (9.33)	37.42 (11.69)	27.70 (9.99)
Services	44.05 (13.87)	70.67 (9.89)	35.11 (9.90)	65.12 (8.13)	29.02 (9.07)	61.67 (8.62)	29.45 (10.60)	60.94 (8.71)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	34.73 (5.07)	38.96 (6.34)	35.22 (4.32)	39.17 (5.69)	34.38 (4.69)	37.32 (5.84)	34.52 (3.97)	37.10 (6.65)
% Female Employment	26.41 (5.44)	41.76 (4.42)	26.68 (5.82)	41.34 (3.81)	25.84 (6.91)	39.45 (3.64)	27.76 (6.29)	39.02 (3.84)
% High Qual. Workforce	3.37 (1.73)	14.85 (4.17)	2.09 (0.88)	12.31 (3.01)	1.41 (0.64)	10.15 (2.84)	1.28 (0.54)	9.61 (2.77)
% Aged 65+	10.42 (2.27)	20.39 (3.29)	11.97 (2.86)	21.08 (2.88)	12.90 (3.08)	21.95 (3.37)	12.61 (2.75)	22.08 (3.97)
LLMs	202	202	223	223	530	530	105	105

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

A.3.4 UK

Table A.8: Characteristics of British Urban, Intermediate and Rural LLMs, 2010 versus 1970.

	Urban		Intermediate		Rural		Rural Remote	
	1970	2010	1970	2010	1970	2010	1970	2010
A. Relative Size (Sample Aggregates, %)								
% of Sample Population	77.19	73.27	19.21	22.55	3.60	4.18	0.96	1.06
% of Sample Employment	77.11	72.53	19.18	23.25	3.71	4.22	0.97	1.04
B. Total Size (Average LLM, 1,000 individuals)								
Population	1548.72 (2197.66)	1716.61 (2520.03)	132.41 (86.76)	187.24 (122.40)	34.89 (14.69)	49.21 (22.90)	26.21 (11.35)	33.25 (13.98)
Employment	792.24 (1168.59)	826.26 (1234.21)	64.22 (43.57)	92.96 (63.79)	17.31 (7.45)	23.57 (11.27)	12.54 (5.16)	15.40 (6.34)
C. Sectoral Structure (Average LLM, %)								
Agriculture	1.49 (1.41)	0.39 (0.35)	8.38 (4.52)	1.84 (1.33)	21.40 (8.56)	5.30 (2.26)	22.37 (10.64)	6.17 (2.88)
Manufact.	44.42 (9.33)	17.79 (4.72)	35.75 (8.66)	19.41 (3.85)	27.04 (8.43)	20.23 (3.16)	22.89 (7.70)	18.74 (3.24)
Services	54.09 (9.45)	81.82 (4.91)	55.87 (7.90)	78.75 (4.42)	51.56 (7.28)	74.46 (3.88)	54.74 (8.02)	75.09 (4.51)
D. Other Characteristics (Average LLM, %)								
Empl.-Pop. Ratio	48.21 (3.34)	46.85 (2.62)	48.18 (2.39)	48.78 (3.00)	49.75 (3.46)	47.78 (2.45)	48.53 (4.32)	46.62 (3.19)
% Female Employment	33.81 (2.29)	47.31 (0.94)	30.28 (2.43)	47.17 (0.94)	25.79 (2.84)	46.81 (0.98)	24.17 (3.52)	47.18 (0.89)
% High Qual. Workforce	7.85 (1.80)	32.01 (8.01)	8.72 (2.24)	31.66 (6.71)	7.63 (2.20)	29.53 (5.61)	8.92 (2.62)	30.22 (4.96)
% Aged 65+	12.78 (2.55)	15.49 (2.68)	14.45 (3.63)	18.66 (3.21)	16.01 (2.36)	22.00 (2.37)	16.89 (2.76)	22.01 (2.85)
LLMs	118	118	125	125	66	66	23	23

Notes: Manufacturing includes extraction and construction, services include public administration. Standard deviations in parentheses. Figures for sample aggregates do not vary within decades. All statistics in panels B–D are weighted by decadal population shares of LLMs.

B Data Supplement

B.1 Introduction

This supplement briefly describes the sources of a decadal panel dataset containing various socioeconomic and geographic variables for local labour markets (LLMs) in France, Germany, Italy and the UK between 1970 and 2010. Specifically, the dataset contains information on the following variables:

- Total employment

- Sectoral employment
- Female employment share
- Degree of rurality
- Population-weighted population density
- Remoteness
- Population-weighted driving distance to urban centres
- Shares of three education groups (low, middle and high)
- Population
- Population shares of the age groups 0–24, 25–44, 45–64 and 65+
- Population shares of foreign residents
- Wages
- Unemployed inhabitants
- Industry employment
- NUTS Region IDs

Information is not complete (i.e., information is missing for some LLMs and decades) for wages, industry employment, unemployed inhabitants, foreign residents and education groups. In particular, the dataset currently does not provide wage data for French and British LLMs, for Italian LLMs before 1990, and for German LLMs before 2000. Moreover, industry employment is not provided for French and German LLMs, information on unemployed inhabitants is not provided for German LLMs and information on foreign residents is not provided for French and Italian LLMs before 1990. Finally, education shares are only fully recorded for shares of high-educated inhabitants. Shares of middle and low educated inhabitants are missing for British LLMs before 2000 and for German LLMs in 1970.

The remainder of this supplement describes the data sources for each available variable by sample country.

B.2 France

B.2.1 LLMs

We draw on 1994 French LLMs (*zones d'emploi*), which are aggregations of French municipalities, based on 1990s commuting data. The classification and aggregation procedure is described in detail in INSEE (1987) and Ronsac (1994). All variables listed below are originally provided at the municipality level. However, because municipalities are nested in LLMs, variables can be easily aggregated to LLM-level information.

B.2.2 Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the French population census, which provides harmonized sectoral employment data for individuals aged 25–54 on the municipality level.[19]

Specifically, we draw on the number of employees in 1982 to approximate employment at the start of the 1980s, on the number of employees in 1990 to approximate employment at the start of the 1990s, on the number of employees in 1999 to approximate employment at the start of the 2000s and on the number of employees in 2011 to approximate employment at the start of the 2010s. To approximate the start-of-decade employment of the 1970s, we use the average number of employees in 1968 and 1975 as the data does not record employment information for years in between.

For consistency, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then aggregate the municipality-level employment data to 1990 employment zones, relying on an official crosswalk. When municipalities cannot be assigned using this crosswalk, they are often merged with other municipalities over time. To merge those formerly independent municipalities, we draw on a file by the French National Statistical Office (INSEE) that tabulates all territorial changes at the municipality level. The few remaining unmerged municipalities are assigned manually to the correct 1990 employment zones.

B.2.3 Female Employment

Total female employment is drawn from the same census data described in Appendix B.2.2. We aggregate this municipality-level information to LLMs using an identical aggregation procedure.

B.2.4 Degree of Rurality

To identify rural areas, we draw on population and surface data at the municipality level in 1968, available via the website of Observatoire Territorial, which is operated by the French government.[20] We then assign municipalities to LLMs using the same procedure as in Appendix B.2.2

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality. First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200,000 and 500,000 inhabitants that represents at least 25% of the LLM population. Finally, we classify an LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500,000 inhabitants that represents at least 25% of the LLM population.

B.2.5 Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Appendix B.2.4. We then go on to compute the LLM-specific population-weighted average of these densities.

[19] See https://www.insee.fr/fr/statistiques/1893185.

[20] See https://www.observatoire-des-territoires.gouv.fr/outils/cartographie-interactive/#c=home.

B.2.6 Remoteness

Based on a second OECD typology (Dijkstra & Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities which exhibit driving distances to the nearest urban centre (a municipality with 50,000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban centre, we draw on Open Street Map data and Stata's OSRM package.

B.2.7 Population-Weighted Driving Distance to Urban Centres

Municipality-level driving distances to urban centres (i.e., municipalities with 50,000 inhabitants or more) are derived from the same data sources as in Appendix B.2.6. We then go on to compute the LLM-specific population-weighted average of these driving distances.

B.2.8 Education Groups

Like sectoral and total employment data, education data come from the French population census that provides education data for individuals aged 25–54 on the municipality level.[21] For consistency, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Appendix B.2.2. Subsequently, we aggregate total employment and the number of people with (1) a higher education degree (*diplôme de niveau supérieur à bac+2*)[22], (2) a medium level of education (*baccalaureat* or vocational degree, for example, CAP and BEP) and (3) a low level of education (no vocational education degree or *baccalaureat*) at the LLM level and calculate workforce shares of low-, medium- and high-educated people, dividing LLM-specific education groups by the sum of these education groups (i.e., the total workforce).[23]

B.2.9 Population

Population data for 1968, 1975, 1982, 1990, 1999 and 2011 on the municipality level are extracted from the Observatoire Territorial. We then assign municipalities to LLMs using the same procedure as in Appendix B.2.2. For consistency, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*).

B.2.10 Age Groups

Like sectoral employment data, age-group data come from the French population census that records municipality populations in age groups. Corresponding data are provided by the French National Statistical Office.[24] For consistency, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Appendix B.2.2. Subsequently, we aggregate the number of people aged 0–24, 25–44, 45–64 and 65+ at the LLM level and calculate age-group shares by dividing each age group's population by the sum of all age groups.

[21] See https://www.insee.fr/fr/statistiques/1893185.

[22] This includes *licence, maîtrise, master, dea, dess, doctorat, diplôme de grande école*. See as well https://www.insee.fr/fr/metadonnees/definition/c1076.

[23] See https://www.insee.fr/fr/metadonnees/definition/c1076.

[24] See https://www.insee.fr/fr/statistiques/1893204.

B.2.11 Unemployment

Like sectoral employment data, unemployment data come from the French population census that records the employment status of individuals aged 25–54 on the municipality level. Corresponding data are provided on the homepage of the French National Statistical Office.[25] For consistency, we exclude all data on DOM-TOMs (*départments and terretoires d'outre mer*). We then assign municipalities to LLMs using the same procedure as in Appendix B.2.2. Subsequently, we aggregate the numbers of unemployed individuals at the LLM level.

B.2.12 NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid.

B.3 Germany

B.3.1 LLMs

We draw on 1990 West-German LLMs (*Arbeitsmarktregionen*), which are aggregations of German districts, based on 1980s commuting data. The classification and aggregation procedure is described in detail in Eckey et al. (1990). All variables listed below are originally provided at the district or municipality level. However, as districts are nested in LLMs, variables can be easily aggregated to LLM-level information.

B.3.2 Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we draw on 1970 census data and employment statistics by the Federal Statistical Office ("Erwerbstätigenrechnung") for 1980, 1990, 2000 and 2009. This dataset reports employment at the district level.

Due to (state-specific) territorial reorganizations in the 1970s, districts recorded in the 1970 census do not correspond to the districts that form the basis of the 1990 German LLMs. We thus use a version of the 1970 census data that has been adjusted to territorial changes and records contemporary districts (Schmitt et al., 1994). In particular, we extract data on total employment by LLM.

Analogous employment data from the *Erwerbstätigenrechnung* for the other years cited above can be accessed via the homepage of the Federal Statistical Office[26] or the German Regional Accounts. We use data from the 2005 revision for 1980 and 1990 and data from the 2010 revision for 2000 and 2009.

B.3.3 Female Employment

Like sectoral and total employment data, 1970 total female employment is drawn from the adjusted version of the 1970 census data cited above. Moreover, we compute district-specific female employment for 1980, 1990 and 2000 from reports of the Federal Office for Building and Regional Planning that have, for example, been used previously by Pischke & Velling (1997). Specifically, we extract female employment in 1980 from Böltken et al. (1995), in 1989 from Böltken et al. (1992) and in 2000 from Böltken et al. (2002). Analogous data for 2010 come from the Regional Database of the Federal Statistical Office.[27]

[25] https://www.insee.fr/fr/statistiques/1893185.
[26] See http://www.statistikportal.de/de/etr.
[27] See https://www.regionalstatistik.de/.

B.3.4 Degree of Rurality

To identify rural areas, we draw on population and surface data on the municipality level from municipal records ("Gemeindeverzeichnis"). Specifically, we draw on 1980 data, owing to the territorial changes mentioned in Appendix B.3.2. We then map municipalities to LLMs via districts, omitting "statistical municipalities" without inhabitants that are not part of a district.

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality. First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200,000 and 500,000 inhabitants that represents at least 25% of the LLM population. Finally, we classify an LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500,000 inhabitants that represents at least 25% of the LLM population.

B.3.5 Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Appendix B.3.4. We then go on to compute the LLM-specific population-weighted average of these densities.

B.3.6 Remoteness

Based on a second OECD typology (Dijkstra & Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities which exhibit driving distances to the nearest urban centre (a municipality with 50,000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban centre, we draw on Open Street Map data and Stata's OSRM package.

B.3.7 Population-Weighted Driving Distance to Urban Centres

Municipality-level driving distances to urban centres (i.e., municipalities with 50,000 inhabitants or more) are derived from the same data sources as in Appendix B.3.6. We then go on to compute the LLM-specific population-weighted average of these driving distances.

B.3.8 Education Groups

Similar to (sectoral) employment data, the 1970 education data are drawn from the adjusted version of the 1970 census data cited above. In particular, we approximate the workforce share of high-educated individuals as the number of respondents with a university degree over the number of inhabitants aged 25 and over.

District-specific education data for 1980, 1990 and 2000 are taken from reports by the Federal Office for Building and Regional Planning. Specifically, we draw on Gatzweiler & Runge (1984) for 1983 education data, on Böltken et al. (1992) for 1989 education data, and on Böltken et al. (2002) for 2000 education data. Analogous data for 2010 are extracted from the Regional Database of the Federal Statistical Office.

In each case, we calculate the workforce share of high-educated individuals as the number of employees with a university degree over the total number of employees. Moreover, we calculate

the district- and decade-specific workforce share of low-educated individuals as the number of employees without vocational or university degrees over the total number of employees.

B.3.9 Population

District-level population data for 1970 are drawn from the adjusted version of the 1970 census data cited above. Population data for 1980 and 1990 come from municipal records ("Gemeindeverzeichnis"). Population data for 2000 and 2010 are extracted from the Regional Database of the Federal Statistical Office.

B.3.10 Age Groups

District-level data on inhabitants in the four age groups 0–24, 25–44, 45–64 and 65+ for 1970 are drawn from the adjusted version of the 1970 census data cited above. As this data only records inhabitants in the age group 0–20 instead of 0–24, we rescale the district-specific age group by a state-specific factor, computed from state-specific age-group shares in 1970.[28] Specifically, we apply the following two-step rescaling procedure. First, we multiply the number of inhabitants in the district-specific age group 0–20 by the state-specific factor $(^{Age_{0-24}}/_{Age_{0-20}})$, where Age_{0-20} are inhabitants aged 0–20 and Age_{0-24} are inhabitants aged 0–24. In a second step, we adjust the original age group 21–44 by subtracting the number of inhabitants in the rescaled age group as well as those in the age groups 45–64 and 65+ from the total number of inhabitants of a district.

Analogous age-group data for 1980 and 1990 come from reports and databases of the State Statistical Offices. In particular, data for the states of Bremen, Lower Saxony, North-Rhine Westphalia, Rhineland Palatinate and Baden-Wurttemberg[29] in 1980 and 1990 and data for Bavaria in 1990 are provided online or directly by the respective State Statistical Office. Moreover, we extract data for the states of Hamburg and Saarland from the state-level information provided by the Federal Statistical Office mentioned above.[30] Data for the states of Schleswig-Holstein in 1980 and 1990 and for Hesse and Bavaria in 1980 are taken from respective State Statistical Yearbooks and reports.[31][32] Finally, we extract data for Hesse in 1990 from Böltken et al. (2001).[33]

Age-group data for 2000 and 2010 are again drawn from the Regional Database of the Federal Statistical Office.

B.3.11 Foreign Residents

Like (sectoral) employment data, district-specific numbers of foreign residents in 1970 are drawn from the adjusted version of the 1970 census data cited above.

[28] The data comes from Table 12411-0012 of the Federal Statistical Office's Genesis Database https://www-genesis.destatis.de/genesis/online.

[29] Data for Baden Wurttemberg in 1980 only record information about the age group 25–49 instead of 25-44. We thus rescale this data using a procedure analogous to the approach described above.

[30] See Table 12411-0012 of the Federal Statistical Office's Genesis Database. Using state-level information is possible as Hamburg encompasses only one district and the 1990 LLM of Saarbrücken comprises all districts of the state of Saarland.

[31] See State Stat. Office of Bavaria (1981); State Stat. Office of Hesse (1981); State Stat. Office of Schleswig-Holstein (1981, 1990).

[32] Data for Hesse and Bavaria in 1980 only record information about the age group 0–14 instead of 0–24 (Hesse) or 25–39 instead of 25–44 (Bavaria). We thus rescale this data using a procedure analogous to the approach described above.

[33] This data only records information about the age group 25–49 instead of 25–44. We again rescale this data using a procedure analogous to the approach described above.

District-specific data for 1980 and 1990 are taken from reports of the Federal Office for Building and Regional Planning. Specifically, we draw on Böltken et al. (1995) for 1980 data and on Böltken et al. (1992) for 1989 data. Analogous data for 2000 and 2010 are extracted from the Regional Database of the Federal Statistical Office.

B.3.12 Wages

District-specific average hourly wages per employee for 2000 and 2010 are contained in German Regional Accounts. We use this data to compute LLM-specific weighted averages, weighting hourly wages per employee by the share of employees and hours of an LLM. Subsequently, we compute LLM-specific hourly real wages, deflating nominal wages by the applicable consumer price index of the central bank.

B.3.13 NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid. For NUTS-1 regions, we merge the city states Bremen and Hamburg (respectively) with the territorial states of Niedersachsen and Schleswig-Holstein and the small territorial state of Saarland with the neighbouring state of Rhineland Palatinate, resulting in 7 instead of 10 German NUTS-1 regions.

B.4 Italy

B.4.1 LLMs

We draw on 1981 Italian LLMs (*Sistemi Locali del Lavoro*), which are aggregations of Italian municipalities, based on 1980s commuting data. The classification and aggregation procedure is described in detail in Sforzi (1997). All variables listed below are originally derived from municipality-level information. However, as municipalities are nested in LLMs, variables are easily aggregated to LLM-level information.

B.4.2 Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the Italian population census that records sectoral employment on the 1981 LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011.[34]

Specifically, we use the number of employees in 1971 to approximate employment at the start of the 1970s, the number of employees in 1981 to approximate employment at the start of the 1980s, the number of employees in 1991 to approximate employment at the start of the 1990s, the number of employees in 2001 to approximate employment at the start of the 2000s and the number of employees in 2011 to approximate employment at the start of the 2010s. We then aggregate the 2011 municipality-level employment data to 1981 LLMs, drawing on an official crosswalk.

In addition to total employment, we also extract employment in different industries.

B.4.3 Female Employment

Total female employment is drawn from the same census data described in Appendix B.4.2. We aggregate this municipality-level information to LLMs using an equivalent aggregation

[34] Corresponding data is provided on the homepage of the Italian National Statistical Office (ISTAT). Data for 1971–2001 can be accessed via the interface on https://www.istat.it/it/archivio/113712, and data for 2011 can be accessed via http://dati-censimentopopolazione.istat.it/Index.aspx?lang=en#.

procedure.

B.4.4 Degree of Rurality

To identify rural areas, we draw on population and surface data on the municipality level in 1971, available via the above-mentioned interface-data by the Italian National Statistical Office.[35] We then assign municipalities to LLMs using the same procedure as in Appendix B.4.2.

Subsequently, we calculate municipality-specific population densities and apply an OECD typology (OECD, 1994) that classifies municipalities as rural if the population density falls below 150 inhabitants per square kilometer. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality. First, we classify an LLM as rural if the share of its population living in rural municipalities exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural municipalities ranges between 15% and 50% or if it contains a city with between 200,000 and 500,000 inhabitants that represents at least 25% of the LLM population. Finally, we classify an LLM as urban if the share of its population living in rural municipalities remains below 15% or if it contains a city with more than 500,000 inhabitants that represents at least 25% of the LLM population.

B.4.5 Population-Weighted Population Density

Municipality-level population densities are derived from the same data sources as in Appendix B.4.4. We then compute the LLM-specific population-weighted average of these densities.

B.4.6 Remoteness

Based on a second OECD typology (Dijkstra & Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote municipalities. Remote municipalities are municipalities that exhibit driving distances to the nearest urban centre (a municipality with 50,000 inhabitants or more) of more than 60 minutes. To calculate the driving distance from each of the municipalities to every urban centre, we draw on Open Street Map data and Stata's OSRM package.

B.4.7 Population-Weighted Driving Distance to Urban Centres

Municipality-level driving distances to urban centres (i.e., municipalities with 50,000 inhabitants or more) are derived from the same data sources as in Appendix B.4.6. We then compute the LLM-specific population-weighted average of these driving distances.

B.4.8 Education Groups

Like total and sectoral employment data, education data come from the Italian population census that records residents with a *diploma* (medium educated) as well as people with a *laurea* degree or above (high educated) on the LLM level between 1971 and 2001 and on the municipality level in 2011. More precisely, data are drawn from the same census data described in Appendix B.4.2. We then assign 2011 municipalities to LLMs using the same procedure as in Appendix B.4.2. Subsequently, we aggregate numbers of medium- and high-qualified residents at the LLM level and calculate education-group shares, dividing the LLM-specific number of people with a medium or high education by the LLM-specific population aged 25 and over.[36] The share of low-educated people is calculated as a residual.

[35] See https://www.istat.it/it/archivio/113712.

[36] See Appendix B.4.10 for information on data sources for age groups.

B.4.9 Population

Population data are available on the LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011. In particular, data are drawn from the same census data described in Appendix B.4.2. We again assign 2011 municipalities to LLMs relying on an equivalent procedure as in Appendix B.4.2 and aggregate data for all years at the LLM level.

B.4.10 Age Groups

Similar to total and sectoral employment data, age-group data come from the Italian population census that records age groups on the LLM level between 1971 and 2001 and on the municipality level in 2011. More precisely, data are drawn from the same census data described in Appendix B.4.2. We then assign 2011 municipalities to LLMs relying on an equivalent procedure as in Appendix B.4.2. Subsequently, we aggregate the number of people aged 0–24, 25–44, 45–64 and 65+ at the LLM level and calculate age-group shares by dividing each age group's population by the sum of all age groups, which is equivalent to the LLM-specific population.

B.4.11 Foreign Residents

Information on foreign residents at the LLM level is available for 2001 and 2010 via the above-mentioned interface-data by the Italian National Statistical Office.[37] Municipality-level data for 1990 are provided directly by the Italian National Statistical Office. We assign 1990 municipalities to LLMs using the same procedure as in Appendix B.4.2. Subsequently, we aggregate the numbers of foreign residents at the LLM level.

B.4.12 Wages

Monthly gross wages for 1991, 2001 and 2011 at the LLM level are provided by the National Social Insurance Institute (INPS). Note that this dataset is only available for 941 out of 955 LLMs (for the remaining LLMs, data would come from less than 10 enterprises). We deflate the wages for each decade by the (January) consumer price index of the respective year, which is reported on the homepage of the Federal Reserve Bank of St. Louis.[38]

B.4.13 Unemployment

Unemployment data are available on the LLM level for 1971, 1981, 1991 and 2001 and on the municipality level for 2011. More precisely, data are drawn from the same census data described in Appendix B.4.2. For consistency, we use data on economically active people looking for employment (*"in cerca di occupazzione"*). We then assign 2011 municipalities to LLMs using the same procedure as in Appendix B.4.2 and aggregate data for all years at the LLM level.

B.4.14 Industry Employment

We extract business-census data on 2-digit 1991 ATECO industries by 1981 LLMs from the above-mentioned interface data by the Italian National Statistical Office for 1971, 1981, 1991 and 2001.[39] For 2011, data on 3-digit ATECO 2007 industries at the municipality level are provided by the Italian National Statistical Office.

[37] See https://www.istat.it/it/archivio/113712.
[38] See https://fred.stlouisfed.org/series/ITACPIALLMINMEI.
[39] See https://www.istat.it/it/archivio/113712.

We then (1) merge municipalities to 1981 LLMs using an official crosswalk and (2) map 3-digit ATECO 2007 to 2-digit ATECO 1991 industries based on official conversion tables to obtain a panel dataset on 2-digit ATECO 1991 industries at the 1981 LLM level. Note that 2-digit ATECO 1991 industries correspond one-to-one to NACE Rev. 1 2-digit industries.

B.4.15 NUTS-Region IDs

We assign each LLM to a NUTS-1 and NUTS-2 region, depending on the location of the LLM centroid.

B.5 UK

B.5.1 LLMs

We draw on 1984 British LLMs (*Travel-to-Work Areas, TTWAs*), which are aggregations of British wards (England and Wales) or postcode sectors (Scotland), based on 1980s commuting data. The classification and aggregation procedure is described in detail in Department of Employment (1984) and Coombes et al. (1986).

Note that we do not extract data for LLMs in Northern Ireland. Moreover, we merge several LLMs for consistency. In particular, we merge the TTWAs Aberdeen and Huntley, Barnstaple & Ilfracombe and South Molton, Bideford and Torrington, Dumfries and Lockerbie, Dunoon & Bute and Islay Mid Argyll, Elgin and Keith, Inverness and Badenoch, Kendal and Windermere, Perth and Crief, Skipton and Settle, Thurso, Sutherland and Wick, as well as Llanelli and Carmarthen.

B.5.2 Total and Sectoral Employment

To derive total and sectoral employment data by LLMs, we rely on the UK population census that records employment data on the travel-to-work-area or enumeration-district level, at least since 1961. Corresponding data are provided by the Office for National Statistics via Nomis[40] or by the UK Data service via Casweb[41] and Infuse[42].

Specifically, we use the number of employees in 1971 to approximate employment at the start of the 1970s, the number of employees in 1981 to approximate employment at the start of the 1980s, the number of employees in 1991 to approximate employment at the start of the 1990s, the number of employees in 2001 to approximate employment at the start of the 2000s and the number of employees in 2011 to approximate employment at the start of the 2010s. As censuses before 2001 provide employment data mostly in the form of 10% samples, we multiply relevant statistics by a factor of 10.

To obtain travel-to-work-area statistics, we map the centroids of enumeration districts to 1984 travel-to-work areas using GIS boundary data provided by the UK data service.[43]

In addition to total employment, we also extract employment in the different industries.

B.5.3 Female Employment

Total female employment is drawn from the same census data described in Appendix B.5.2. We aggregate this data to LLMs using an equivalent aggregation procedure.

[40] See https://www.nomisweb.co.uk/.
[41] See http://casweb.ukdataservice.ac.uk/.
[42] See http://infuse.ukdataservice.ac.uk/.
[43] See https://borders.ukdataservice.ac.uk/bds.html.

B.5.4 Degree of Rurality

To identify rural areas, we primarily draw on population data at the ward level[44] from the 1971 Census as well as on surface data from 1971 boundary data.[45] We then assign wards to LLMs using the same procedure as in Appendix B.5.2.

Subsequently, we calculate ward-specific population densities and apply an OECD typology (OECD, 1994) that classifies wards as rural if the population density falls below 150 inhabitants per square kilometre. Relying on the same OECD typology, we then divide LLMs into three types depending on their degree of rurality. First, we classify an LLM as rural if the share of its population living in rural wards exceeds 50%. Second, we classify an LLM as intermediate if the share of its population living in rural wards ranges between 15% and 50% or if it contains a city with 200,000 to 500,000 inhabitants that represents at least 25% of the LLM population. Finally, we classify an LLM as urban if the share of its population living in rural wards remains below 15% or if it contains a city with more than 500,000 inhabitants that represents at least 25% of the LLM population.

B.5.5 Population-Weighted Population Density

Ward-level population densities are derived from the same data sources as in Appendix B.5.4. We then compute the LLM-specific population-weighted average of these densities.

B.5.6 Remoteness

Based on a second OECD typology (Dijkstra & Poelman, 2008; Brezzi et al., 2011), we classify an LLM as remote if 50% of its inhabitants or more live in remote wards. Remote wards are those that exhibit driving distances to the nearest urban centre (a municipality with 50,000 inhabitants or more) of more than 60 minutes.

To identify urban centres, we draw on 1971 population data at the district level ("UK municipalities"), excluding all rural districts (these districts do not contain cities, but are composed of multiple smaller entities) as well as some other districts that do not contain a city with 50,000 inhabitants or more.

To calculate the driving distance from each of the wards to every urban centre, we draw on Open Street Map data and Stata's OSRM package.

B.5.7 Population-Weighted Driving Distance to Urban Centers

Ward-level driving distances to urban centres (i.e., municipalities with 50,000 inhabitants or more) are derived from the same data sources as in Appendix B.5.6. We then compute the LLM-specific population-weighted average of these driving distances.

B.5.8 Education Groups

Education data come from the same census data described in Appendix B.5.2.

We classify employees as high-qualified if they have a degree. This includes individuals with degrees or above in 1971, individuals with degrees or professional vocational qualification in 1981, individuals with diplomas, degrees or higher degrees (levels a, b and c) in 1991, individuals aged 16–74 with a level-4 qualification in 2001, as well as individuals aged 16 or more with a level-4 qualification in 2011.

[44] We use population figures at the ward instead of the enumeration-district level when defining the degree of rurality as this is common practice in similar calculations by the OECD or EU.

[45] See https://borders.ukdataservice.ac.uk/bds.html.

To derive an indicator for the workforce share of high-qualified inhabitants, we divide the number of high-qualified inhabitants by the population in an LLM aged 25 and over for all years except for 2001.[46] For 2001, we use the number of inhabitants aged 25–74 as the education data are only recorded for inhabitants aged 16–74.

For 2001 and 2010 we also derive the workforce share of medium-qualified individuals, dividing inhabitants with level-3 qualifications by the number of inhabitants aged 25–74 (2001) or 25 and over (2010) and calculate the workforce share of low-qualified individuals as a residual.

Subsequently, we aggregate data at the LLM level, relying on a procedure equivalent to that in Appendix B.5.2.

B.5.9 Population

Population data come from the same census data described in Appendix B.5.2. We then aggregate data at the LLM level, relying on a procedure equivalent to that in Appendix B.5.2.

B.5.10 Age Groups

Age-group data (0–24, 25–44, 45–64 and 65+) come from the same census data described in Appendix B.5.2. We then aggregate data at the LLM level, relying on an equivalent procedure as in Appendix B.5.2.

B.5.11 Foreign Residents

To approximate the number of foreign residents, we use data on individuals by country of birth, based on the same census data described in Appendix B.5.2. We then aggregate data at the LLM level, relying on an equivalent procedure as in Appendix B.5.2.

B.5.12 Unemployment

Unemployment data come from the same census data described in Appendix B.5.2. We then aggregate data at the LLM level, relying on an equivalent procedure as in Appendix B.5.2.

B.5.13 Industry Employment

We extract data from the Business Register and Employment Survey (BRES), which is available via Nomis.[47]

For 1992 and 2001, the UK standard industry classification (SIC) 1992 is identical to NACE Rev. 1 up to at least the 2nd digit. For 1971, BRES records data on the 2-digit SIC 1968, for 1981 it records data on the 2-digit SIC 1980 and for 2011 it records data on the 4-digit SIC 2007 level. We use proportional crosswalks by Jennifer Smith[48] to map these classifications to SIC 1992/NACE Rev. 1. For the years before 2011, data are available at the travel-to-work-area 1984 level. Since the 2011 data are only available at the enumeration-district level, we again map centroids of enumeration districts to travel-to-work areas.

B.5.14 NUTS-Region IDs

We assign each LLM to a NUTS-1 and a NUTS-2 region, depending on the location of the LLM centroid.

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[46] See Appendix B.5.10 for information on age-group data sources.

[47] See https://www.nomisweb.co.uk/.

[48] See https://warwick.ac.uk/fac/soc/economics/staff/jcsmith/sicmapping/resources/proportional.