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On the Peripheral-Urban Wage Gap in Germany

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Abstract

We compare real wage differences between centralized and peripheral areas and highly centralized and peripheral areas using vast information of German administrative data that contains more than 2.8 Mio individuals and 660,000 firms. We provide substantial empirical evidence that most of the wage gaps can be explained by differences in endowments of individual and firm characteristics, particularly when unobserved individual and firm heterogeneity is appropriately accounted for. Our interpretation is that the selectivity of workers and firms in space explains most of the real wage gap between peripheral and (highly) centralized regions, and returns to characteristics are honoured rather equally in all regional types.

JEL:
J31 Wage Level and Structure / Wage Differentials
R12 Size and Spatial Distributions of Regional Economic Activity

Keywords

Rural-urban wage gap, Oaxaca-Blinder decomposition, firm characteristics, wage equation

1. Introduction

The phenomenon of an urban-rural wage gap already fascinated economists such as List (1838), Roscher (1878), and Marshall (1890). Since these early days, the interest in this matter has never ceased. Nowadays, it is widely accepted that a wage gap between urban and rural labour markets exists in all countries. The most important reason for this is that the average firm productivity increases with density (Niebuhr & Peters, 2020). Density increases the flow of information, which is part of the well-known urbanisation and localisation externalities (Duranton & Puga, 2020). There is no doubt that the distribution of firms and workers in space is endogenous because it is driven by selectivity and sorting of economic activity in space, e.g. regional differences in migration and start-up activities (Brunow and Nijkamp 2019, Niebuhr et al. 2019). This phenomenon is well known and explained in various New Economic Geography and New Growth Theory models.

So far, many papers have tackled the urban-rural wage gap as a continuum, estimating a factor that measures how density explains this wage gap. However, given the fundamental differences between rural (peripheral) and urban (central) regions, the question arises why this coefficient should have the same value in rural areas as in agglomerations? Therefore, we start from the assumption that it is not a continuous phenomenon. Consequently, we estimate separately for different categories of regions.

By doing this in a peripheral-centralized comparison, we raise two questions: What part of the wage gap can be explained by observed characteristics at the individual and firm level, and how much of the wage gap is explained by the differential returns to such characteristics? To this end, we use the methodology developed by Oaxaca (1973) and Blinder (1973). This method has been widely used to examine “discrimination” in labour markets, e.g. women, black worker. We use this method to break down the average wage gap between peripheral, centralized, and highly centralized labour markets into differences explained by the variables included in the models and those explained by the model's coefficients.

The paper is structured as follows. Section 2 reviews literature focussing on reasons for differences and explanations between peripheral and centralized regions. Section 3 introduces the data basis and motivates variables that have to be considered to account for issues presented in the literature section properly. Section 4 presents our identification strategy in detail. A descriptive picture and the results are presented in Section 5. Section 6 concludes.

2. Literature Review

The rural-urban wage gap is mostly explained by productivity differences, human capital spillover-effects and selectivity of workers and firms (Henderson et al. 2001; Rice et al. 2006; Saito & Gopinath 2009). Especially density promotes external effects that enhance the productivity of firms and workers. Localisation economies, the concentration of firms from the same industry (MAR externalities), and urbanisation economies, the concentration of firms of different industries (Jacob’s externalities), localized human capital and knowledge spillover effects are at work, enhancing the productivity of firms and individuals (Glaeser et al. 1992; Glaeser et al. 2014; Combes & Gobillon 2014; Brunow & Blien

2015; Rosenthal & Strange 2004). Duranton and Puga (2004) distinguish between three phenomena to explain the urban-rural productivity gap, connected with the size of the markets. First, a larger market results in a larger variety of possible suppliers. Second, a larger market also allows for better matching of employers and workers or buyers and suppliers. Third, a larger market may also facilitate learning by encouraging the transfer of skills and fostering innovation and new technologies. In this light, the New Economic Geography and the New Growth Theory provide theoretical channels, which show how agglomeration forces can lead to persistent wage differentials (Krugman 1991, Baldwin et al. 2004; Grossman & Helpman 1991).

The early work of Haltiwanger et al. (1999) provides empirical evidence of the impact of firm size, human capital and workforce composition on firm productivity. However, this paper does not include any regional variation. Brunow & Blien (2015) show the impact of intra-industrial externalities on firm productivity especially, how regional density impacts firm productivity. However, the endogeneity-question remains, as selection is not controlled for and it is well known that firm productivity is higher in agglomerated regions and associated with the workforce composition (Combes et al. 2004; Trax et al. 2015; Brunow & Blien 2014).

There is plenty of literature documenting the substantial growth of wage inequality during the last decades. One reason for this development is the skill-biased technological change (Autor et al. 2006; Goos et al. 2009), which leads to growing structural changes between the income distributions of jobs requiring different skills. Especially the demand increased for jobs that need high qualifications while at the same time, the number of university graduates decreased. Furthermore, the labour market institutions eroded, especially the binding force of trade unions decreased (Ellguth & Kohaut 2019). This increasing job polarization also contributed to the growth of rural-urban wage inequality because the job polarisation is much stronger in cities as routine biased technological change is mainly an urban phenomenon (Dauth 2014).

Besides structural differences between urban and rural locations, sorting processes are responsible for the urban-rural wage gap. For example, some industries rely more on centrality than others, and some individuals value typical urban amenities more than others. The classic question that arises here is if workers move to get a job or vice versa. A recent meta-study analyses the evidence of 64 studies and concludes that although the evidence is highly divergent, there is a tendency for jobs to follow workers (Hoogstra et al. 2017). This would suggest that the workers' regional preferences influence the sorting of jobs between urban and rural locations more than vice versa. Fuchs et al. (2021) document a large variation in the gender pay gap in Germany depending on the region under consideration. Thus, there is first evidence of spatial sorting of females and males but also of firms in space, leading to such variation.

Therefore, an important question is the extent to which urban-rural wage disparities are due to the skill composition of the workforce or due to non-human endowments, such as infrastructure, etc. Combes et al. (2008) conclude that differences in the skill composition of the workers account for up to 50% of the spatial wage disparities. De la Roca and Puga (2017) find that workers' wages are not initially higher in larger cities; instead, it is mainly work in cities of different densities that causes their income to diverge over time. Thus, even if a selection is taken into account, workers benefit from specific experiences, which increase with density. This mechanism penalises workers in rural areas that, even if they have the same productivity to start with, are less able to increase their experiences and fall relatively behind a comparable person who works in a city. A recent study by Hamann et al. (2019), using rather similar data to this study, shows that a doubling of employment density increases wages for new hires between 1.0% and 2.6%, depending on their status before new employment.

However, these studies do not address a specific analysis of the differences between urban and remote areas. In particular, differences in accessibility play a central role. Spatially monopsonized (or oligopsonized) labour markets pose problems, especially for workers who are time-restricted. Time restrictions apply to significantly more women than men. Hirsch et al. (2013) provide evidence for specific discrimination of women in rural areas. Women are especially disadvantaged by living in a remote area because firms possess some monopsony power in such areas, as employers are less widespread than in cities and work includes higher travel costs. These are especially high for many women, as they are traditionally still less mobile than men due to household obligations. This causes an extra discount on wages for women in rural areas. The womens' discrimination between urban and rural areas is constantly about 10% during the last 30 years, according to Hirsch et al. (2013).

When analyzing rural-urban wage differentials, it is vital to consider the different cost levels in both categories. Density constitutes urban space and thus dictates the scarcity of space for living and working, which translates into higher costs. Hence, it comes as no surprise when Weinand and von Auer (2020) state that price differentials are mainly driven by housing, and according to the authors' the most expensive of the German districts exceeds the cheapest by 161%. Nominal wages, therefore, reflect the true material standard of living only to a very limited extent. If higher wages merely compensate for higher costs in cities, employees gain nothing, at least in real material terms. However, most studies used nominal wages in the absence of sufficient data on the different cost levels. A notable exception for Germany is the study of Kosfeld et al. (2008). The authors show that an analysis based on real wages is particularly important in the formerly divided Germany. The economic differences between the former socialist GDR and the capitalist FRG are still very pronounced, at least until 2004, the most recent state of this paper. However, even 30 years after reunification, the economic gap between the two parts of the country has not yet been overcome, and a comparison of regional nominal wages would not adequately capture the differences in prosperity between East and West.

Based on the literature on agglomeration economies, we assume that more factors explain the rural-urban wage gap. Besides individual characteristics, firm characteristics have to be taken into account (Dostie et al. 2020). In contrast to existing literature that uses the between-regional-types variation to explain wage differentials, we focus on regional-type specific wage setting and explain the wage gap by observed characteristics. We hypothesize that rural-peripheral labour markets differ significantly from urban-central labour markets. Therefore, our approach is to estimate different equations for urban and rural environments that allow us, after an Oaxaca-Blinder decomposition, to learn about the nature of urban and rural labour markets and potential returns to the factors we consider. This approach allows us to test our basic assumption that agglomeration benefits do not simply radiate linearly from the centres to the periphery. Rather the elasticities of the production factors employed change between the different localities as a function of centrality.

3. Data and variables

The analysis exploits administrative data of a cross-section of 10% of all full-time employees working subject to social security contributions in Germany in 2018 and contains more than 2.8 Mio individuals. The data basis includes almost all employees except civil servants and self-employed. The Institute for Employment Research (IAB) provides the data basis, i.e. the "Integrated Employment Biographies" (IEB). We observe entire employment-unemployment biographies and construct several characteristics describing individual performance at the labour market (see Table 2). Additionally, with a unique identifier, each worker is assigned to firms (establishment). Therefore, not just individual but also firm-level data can be analysed. Table 1 provides an overview of the number of individuals and firms on which we build the analysis.

Table 1: Sample information and Number of individuals and firms

	Total	**Highly centralized**	**Centralized**	**Peripheral**
No. of individuals	2,865,284	1,469,926	839,832	555,526
No. of plants	661,177	313,714	200,834	146,629

Data basis: "Integrated Employment Biographies" provided by the IAB.

Our dependent variable is the individual real wage, calculated by deflating nominal wages by a regional price index (Weinand and von Auer (2020), see section 4). Each employment period records information on the gross daily nominal wages. These data are very reliable as it is used to compute social security benefits and the retirement pension. Unfortunately, the nominal wages are truncated at an upper limit above which no additional social security contributions have to be paid. We apply a wage imputation developed by Card et al. (2013) to circumvent this restriction to impute the truncated wages.

To explain regional wage differentials, we consider the following variables as essential (see Table 2): At the individual level, we control for age, gender, educational and vocational attainment and distinguish between Germans and foreigners as standard characteristics. However, these measures are potentially poor proxies to capture individual heterogeneity. These unobserved characteristics may be important in explaining wage differentials, and omitting such variables would lead to biased estimates. If there is a specific selectivity of such unobserved features in space, we might draw wrong conclusions about observed features correlated with the unobserved part in terms of content. To consider such individual heterogeneity, we compute various measures of performance in the labour market based on the entire individual's employment history. However, even if these measures capture much more of the individual heterogeneity, not every characteristic is observable for us– such as differences in personality or cognitive ability. Card et al. (2013) provide a measure, which captures and identify an individual's but also firm's unobserved heterogeneity based on individual and firm fixed-effects regressions (CHK-effects)[1]. These coefficients are identified on an individual level and at the firm level, captured in two separate variables, and are provided by the IAB. This enables researchers

[1] The measure consists of two parts. The first part is interpreted as the person effect, a combination of skills and other factors that are rewarded equally across employers. The second part is interpreted as the proportional pay premium (or discount) that the firm pays to all employees.

to address and extend the issue of unobserved heterogeneity of individuals and firms in a cross-sectional investigation.

Because of the spatial dimension of the skill-biased polarization of jobs and wages, we control for differences in occupations at the 2-digit level (37 categories). Additionally, we distinguish skill-biased regional differences in tasks. These are unspecialized tasks, specialized tasks and specialists/experts but also a foreman-position and tasks requiring leadership qualities and team responsibility.

With respect to regional differences, we distinguish between three types: peripheral, centralized, and highly centralized regions. The definition of peripheral regions is ambiguous. Mostly, it is defined by the absence of density, leaving it as a residual category. We focus on centrality because the centrality of agglomerations radiates to the surrounding areas, not only in terms of accessibility but also in terms of the cost structure. Housing, in particular, is significantly more expensive in the vicinity of larger agglomerations than in peripheral regions with the same density.

We use a long-established regional classification provided by the German Federal Institute for Research on Building, Urban Affairs and Spatial Development (BBSR). This classification distinguishes NUTS-3 regions ("Kreise" and "Kreisfreie Städte") based on accessibility and population density into three classes: peripheral regions are primarily remote; centralized regions are moderately densely populated regions, mostly in the hinterland of the core cities; and thirdly the core-cities, the highly centralized regions. This means that we do not treat the rural areas in the hinterland as peripheral regions. Hence, low-density regions are found in all three categories. Figure 1 shows the assignment of each region to a specific regional type.

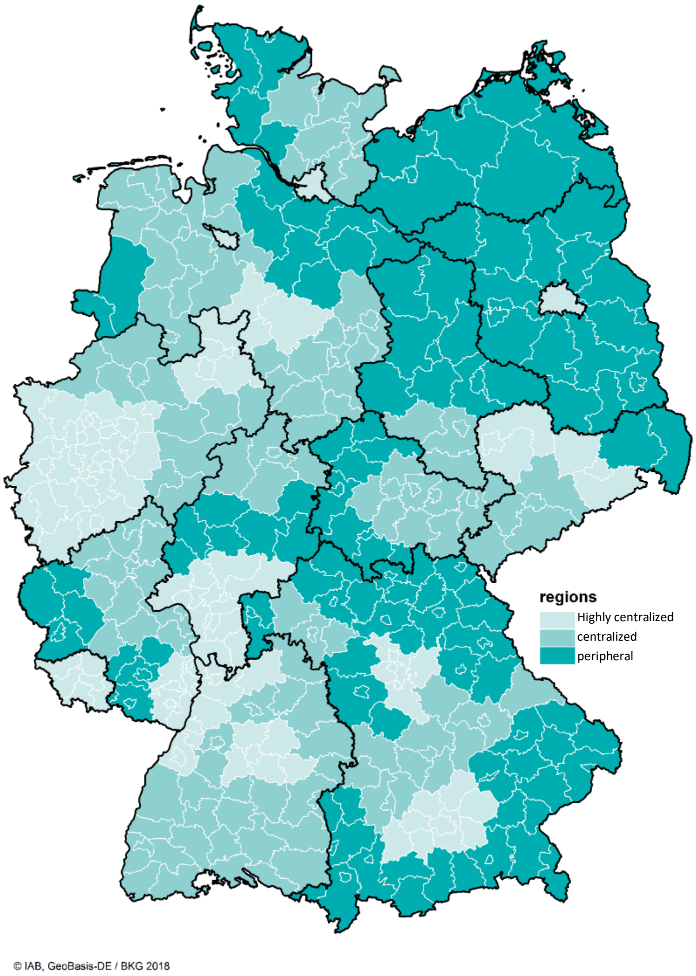

Figure 1: Regional assignment to regional types (402 districts, NUTS III)

As shown in section 2, regional wage differentials can result from differences in firm characteristics, such as size and workforce composition in terms of age diversity, cultural diversity, human capital intensity, and others (e.g. Dostie et al. 2020; Brunow & Jost 2021). We take most of these differences into account and explain differences in individual wages on that basis. As was the case at the individual level, unobserved firm characteristics such as specific managing strategies, tariffs, and the impact of union coverage may influence the overall productivity and, thus, differences in employees' wages. Therefore, we consider the CHK firm effects. Table 3 reports all firm characteristics we employ in the decomposition of the wage structure.

Table 2: Individual characteristics

Variable		Description
Wages (dependent variable)		
	Daily real wage	Nominal wage deflated by the regional price index (Weinand & von Auer (2020)
Personal characteristics (INDIVID)		
	Gender	Indicator of gender (1=female, 0=male (ref.))
	Foreigner	Indicator of nationality (1=foreign, 0=German (ref.))
	Age	Categorical variable representing the individual's age grouped into five age brackets: 16–24 years old, 25–34 years old, 35–44 years old (ref.), 45–54 years old, 55–64 years old

Individual educational attainment and vocational training (EDUC)		
	School-leaving certificate*	Categorical variable of highest school certificate, consisting of three groups: no school graduation, intermediate school-leaving certificate (ref.) and upper secondary school-leaving certificate (Abitur//higher education entrance qualification)
	Vocational Education*	Categorical variable of highest vocational qualification, consisting of three groups: no vocational qualification, vocational education (ref.) and training (VET)[2], and university degree
	Foreman	Indicator of further job qualification (German "Meister/ Polier")
	* a correction procedure was applied for both variables (Fitzenberger et al. (2005))	
Individual labour market experience (EXP)		
	Observed time in data	Categorical variable indicating four quantiles of the distribution of years observed in the data
	Share of non-employment in the data	Categorical variable representing the share of time observed in which a worker was not in employment: < 5 % (ref.), > 5 % and < 10 %, > 10 % and < 25 %, and > 25 % and < 75 %
	Ln mean duration	Log of no. of years working per firm
	Ln firm duration	Log of years working in current firm
	No. of firms	Number of different employers during work-life
Individual selectivity-related variables on industry and occupation		
	Occupation (*OCC*)	Categorical variable encompassing 50 occupations according to the occupational classification system KldB 2010 (related to ISCO-08)
	Industry (*IND*)	Categorical variable encompassing 96 distinct industries at the 2-digit level according to the German classification scheme WZ 2008 (NACE Rev. 2.)
Individual task content of current job (TASK)		
	Task level	Categorical variable representing three different task levels of the job. It consists of three groups: auxiliary activity (unskilled task), trained/professional task (clerks; ref.), and specialist/expert task
	Supervisor	Dummy variable indicating whether an employee is a supervisor (=1)
	Executive	Dummy variable indicating whether an employee is an executive (=1)

Table 3: Firm characteristics

Firm Characteristics: Economies of Scale (Firm Scale)		
	Firm size indicator	Categorical variable measuring firm size build on the number of employees: less than 10 employees (ref.), 10 to less than 50 employees, 50 to less than 250 employees, 250 employees and more.
Firm Characteristics: Workforce Diversity (Firm-Div)		
	Share Females	Proportion of females among all employees
	Share young workers	Proportion of workers of age less than 35 years
	Share mature workers	Proportion of workers of age 55 years and higher
	Share Complex Tasks	Proportion of workers employed as Specialists and Experts (i.e. human capital intensity)

[2] The system of Vocational education and training (VET) is rather unique in the international context. The training takes place in private firms and is combined by education in public schools. This training usually lasts 3 years.

	Foreigner Employment	Categorical variable[3] capturing the proportion of foreign employees (categorization is based on the empirical distribution) No foreigners employed (ref.), larger than 0% to less than 5%, 5% to less than 10%, 10% to less than 15%, 15% to less than 20%, 20% to less than 30%, 30% to less than 50%, 50% to less than 75%, 75% to 100%
Card-Heining-Kline CHK (2013) individual and firm effects		
	Individual Effects	Individual CHK effects to control for overall unobserved individual characteristics
	Firm Effects	Firm CHK effects to control for overall unobserved firm characteristics
Note: ref.=reference category		

4. Identification Strategy

Our identification strategy contains two important aspects; the real wage and the Oaxaca-Blinder decomposition. Using wages adjusted for differences in price levels between centralized and peripheral areas allows a rational analysis of the true impact on these wage differentials relevant for individuals. We can base our estimates on real costs by drawing on data recently published by Weinand and von Auer (2020). The authors use data on the German consumer price index collected from about 400 different regions. This data includes the prices of all individual products and several attributes that identify products and their outlet types. It also comprises a large sample of rents and details about the flats and houses. The authors are convinced that "though not designed for the purpose of regional price comparisons, worldwide it is probably the best data source for that purpose" (Weinand and von Auer, 2020:414). The price index data is disaggregated regional price index on the district level (NUTS III) and has been used by Rokicki et al. (2021) to estimate real wage dispersion in German regions.

Using the Oaxaca-Blinder decomposition (OBD) method, we decompose wage differentials $\widehat{w_c} - \widehat{w_p}$ into three components: endowment effect, coefficient effect, and interaction effect; see equation (1). The OBD method is widely used to identify and explain a wage gap between two groups (Oaxaca 1973; Blinder 1973). In light of our study, we consider three groups (peripheral, centralized, and highly centralized regions) to compare the latter two groups separately with the first one. For each comparison group, an individual wage equation is estimated using OLS, with identical controls. This provides group-specific parameter vectors on the returns or influence of each variable on wages for either centralized or highly centralized regions ($\widehat{\beta_c}$), respectively, and peripheral regions ($\widehat{\beta_p}$). Jann (2008) provides a formal description of the OBD including further details of the following.

$$\widehat{w_c} - \widehat{w_p} = \widehat{\beta_c}\overline{X_c} - \widehat{\beta_p}\overline{X_p} = \underbrace{\left(\overline{X_c} - \overline{X_p}\right)\widehat{\beta_p}}_{Endowment} + \underbrace{\left(\widehat{\beta_c} - \widehat{\beta_p}\right)\overline{X_p}}_{Coefficient} + \underbrace{\left(\overline{X_c} - \overline{X_p}\right)\left(\widehat{\beta_c} - \widehat{\beta_p}\right)}_{Interaction} \tag{1}$$

The *endowment effect* explains the difference in wages due to the different distribution of observed characteristics in space. If $\overline{X_c}$ and $\overline{X_p}$ are vectors of average observed characteristics, then the

[3] The literature on foreign employment and cultural diversity provides evidence on a non-linear relationship between foreign employment and firm success measures such as productivity. Because this is linked to wage setting, we employ a categorical approach instead of the proportion (and its squared value) to account for the nonlinearity.

endowment effect considers the difference $\left(\overline{X_c} - \overline{X_p}\right)$. Multiplying these differences by a parameter vector yields a measure for the endowment effects for each explanatory variable. For example, using the peripheral parameter vector as reference, $\left(\overline{X_c} - \overline{X_p}\right)\widehat{\beta_p}$, can be interpreted as follows: How much would the average peripheral worker earn more (or less) if his/her characteristics are adjusted to the average value of a centralized or highly centralized worker. If these effects prevail, mainly the unequal distribution of individual and firm characteristics between the areas drives the differences in real wages.

The difference in parameters between the two groups relates to the *coefficient effect*. This effect predicts the wage difference due to differences in parameters between peripheral and centralized regions for a given characteristic. Differences in coefficients reveal structural differences in the benefits of a characteristic under consideration. If, for instance, the estimated coefficient for age is larger in centralized or highly centralized regions, an additional year of age would provide a higher increase in wages in centralized or highly centralized regions, and thus, the returns of ageing are higher in cities. Because our primary interest is the peripheral perspective, we evaluate the coefficient effect of the average characteristics of people in peripheral areas. The interpretation is then: How much would an average individual earn more (or less) if its coefficients were adjusted to the coefficients of the centralized or highly centralized region, i.e. $\left(\widehat{\beta_c} - \widehat{\beta_p}\right)\overline{X_p}$. This can be interpreted as the "penalty" for living in a rural region.

Finally, the interaction effect considers both the adjustment of characteristics and parameters in a multiplicative setting. This effect becomes zero if the endowment or coefficient effect is zero; the wage gap can be explained entirely by the endowment or coefficient effect only. Interaction effects can be positive or negative and will usually be analysed if they are substantial.

To secure valid interpretations of OBD results, the comparison groups need a sufficient overlap in the distribution of the explanatory variables. The overlap secures that the estimated coefficients ($\hat{\beta}$) do not differ just because they are estimated for different value ranges of X's (Borjas, 1987). Thus, an a-priori assignment into groups, which already takes differences in various regional characteristics into account, such as innovativeness and differences in the human capital intensity, would lead to groups consisting of different value ranges, making the OBD invalid. In the next section, we discuss the results of the OBD.

5. Results

Descriptive Analysis

Figure 2 visualizes the regional distribution of real gross daily wages over Germany. Each of the five groups contains approximately 20% of all regions (thus, quintiles). As shown, there is a wage gap between East and West Germany and a North to South gap. However, not necessarily highly centralized areas offer the highest wages, followed by centralized and lastly peripheral regions. There are, for instance, relatively good paid peripheral regions in the south but also less good paid centralized regions. Thus, we observe an overlap in the wage distribution and – as provided next – also in the characteristics that explain the wage differential. The overlap is important to secure an overlap in observed characteristics between the regional types and not to compare "pears with apples".

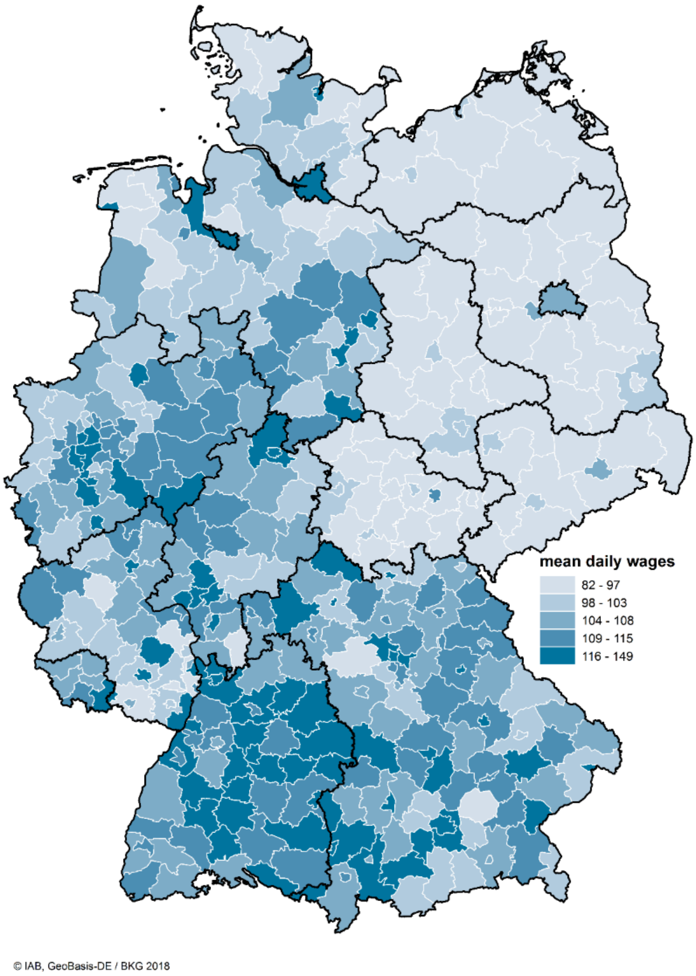

Figure 2: Regional distribution of real gross daily wages

Table 4 provides a descriptive picture of average wages separated by individual characteristics. As can be seen, wages are on average highest in highly centralized regions, followed by centralized regions and peripheral regions. The same picture holds for real wages. However, this relationship becomes more diverse when variables at the individual level are considered. For example, differences in real wages for unskilled tasks show no difference in wages between highly centralized and peripheral regions.

The unconditional gender pay gap is almost identical between the regional types and ranges between 84.2 to 87.4 per cent. The unconditional immigrant-native earnings gap ranges from 78.5 per cent in highly centralized regions over 79.8% in centralized to 82.9% in peripheral regions.

Table 4: Descriptives on (real) wages and individual characteristics

		Regional Type		
		Highly centralized	**centralized**	**peripheral**
gross daily nominal wage	mean	122.26	111.8	102.55

	(s.d.)	(56.43)	(50.65)	(46.51)
gross daily real wage	Mean	118.88	113.45	105.44
	(s.d.)	(54.39)	(51.12)	(47.71)
No. Individuals		1,469,926	839,832	555,526
Means of real wages separated by…				
… tasks				
unskilled tasks		77.66	79.99	75.88
skilled tasks		107.21	105.63	98.52
specialists/experts		156.56	156.21	147.07
… leadership responsibilities				
no specific responsibilities		115.75	110.25	102.44
supervisor		150.82	151.76	139.75
executive		175.77	177.73	168.14
… gender				
Male		123.84	119.13	109.84
Female		108.7	99.98	95.36
… nationality				
Natives		125.39	117.83	108.25
Foreigners		100.68	97.07	92.18
… individual age				
<25		80.6	84.13	83.25
25-34		107.05	104.37	97.44
35-44		121.65	115.76	106.68
45-54		128.85	121.29	112.08
55+		128.25	120.36	111.02
… Occupational education				
no vocational training degree		90.13	86.54	83.54
vocational training degree		114.6	111.25	102.57
foreman		137.36	135.69	126.61
academic degree		161.76	165.65	158.38
Individual heterogeneity				
CHK individual effects (mean)		0.099	-0.063	-0.168
(s.d.)		(1.044)	(0.957)	(0.910)

Regarding age, the wage profile is flatter in peripheral regions, indicating that jobs may offer fewer gains because of "on-the-job-training" and specialized job-specific knowledge. In this spite, returns to education are lower in peripheral regions, but for academics, little differences occur. The CHK effects are individual-specific values collected in a single variable to capture overall unobserved heterogeneity. A clear pattern emerges: in highly centralized regions, individuals show higher values compared to centralized and, lastly, peripheral regions, providing evidence of more productive workers located in highly centralized areas. Interestingly, there is a broader distributed individual unobserved heterogeneity in highly centralized regions, while in peripheral regions, the distribution is more homogeneous.

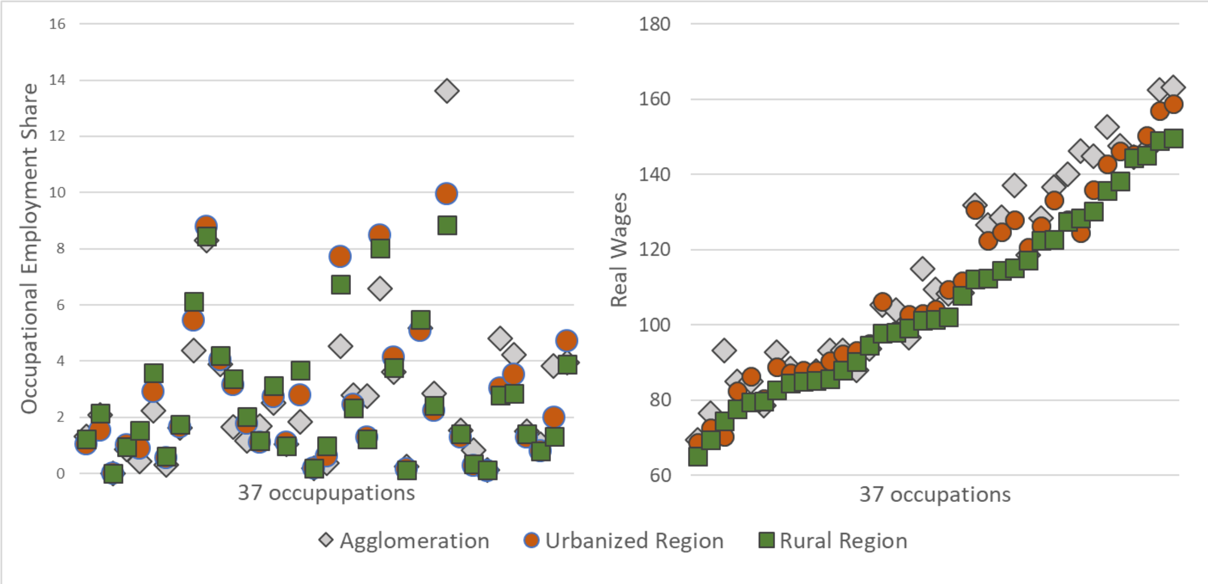

Figure 3: Occupational mix and real gross daily wages by regional types

Fehler! Verweisquelle konnte nicht gefunden werden. visualizes the occupational mix (left panel) and real wages (right panel) among the 37 2-digit occupations, sorted from the smallest to the largest real wage in peripheral regions. With few exceptions, there is no obvious deviation in the occupational mix between the three regional types. Real wages, however, are in almost all cases lowest in peripheral regions and higher in the other two regional types. In most cases, real wages are highest in highly centralized areas.

Table 5 provides a descriptive picture of firm characteristics. Interestingly, there is no noticeable difference in the firm size distribution between the three regional types. In addition, the proportion of females and young workers is, on average, rather equal. Thus, not necessarily younger workers tend to prefer regions with better opportunities, i.e. centralized and highly centralized regions. There is a slightly higher share of older workers in peripheral regions relative to highly centralized, but with 2.6% not very pronounced. However, given the higher wages in highly centralized areas, it is not surprising that they are more attractive for immigrants, and thus, the proportion of foreigners employed in highly centralized regions is substantially higher than in peripheral regions. The human capital intensity of large cities is also substantial: On average, the proportion of specialists and experts in highly centralized areas is about 6 to 8 per cent higher compared to centralized and peripheral regions. Lastly, the CHK firm effects are higher in highly centralized areas, followed by centralized and peripheral regions. Thus, potentially more productive firms concentrate in highly centralized regions, while firm productivity seems lower in peripheral regions. As for individual effects, firm effects vary more in highly centralized and centralized regions compared to peripheral regions.

The descriptive picture shows first evidence that differences in the distribution of characteristics in the respective regional types are not too pronounced. Concerning wages, the nominal wage gap reaches up to 26 Euro gross daily income, depending on the occupation. So far, no clear pattern in the regional distribution of individuals and firms can be drawn. However, there is first evidence of a specific regional selectivity of (un)observed individual and firm characteristics. Especially individuals and firms in highly centralized regions show higher values of CHK effects relative to centralized and, lastly, peripheral regions. To disentangle the effects, the OBD will be applied in the next section.

Table 5: Descriptives on firm characteristics

	Regional Type Highly centralized	centralized	peripheral
No. of plants	313,714	200,834	146,629
Separated by firm size (distribution in percent)			
<10 employees	52.77	52.32	53.81
10 to <50 employees	34.46	35.71	35.37
50 to <250 employees	10.76	10.35	9.48
250 employees and more	2.02	1.62	1.34
Average proportion of…			
… females	40.7%	40.0%	40.1%
… young workers (<35years)	33.8%	32.9%	31.4%
… older workers (55+ years)	16.3%	17.7%	18.9%
… specialists/experts	27.8%	20.7%	19.4%
… foreigners	16.7%	11.6%	9.1%
CHK Firm effects (mean)	-0.289	-0.399	-0.589
(s.d.)	(1.191)	(1.116)	(1.095)

Estimation results

Motivated by a Mincer wage equation, we regress variables as reported in Table 2 on the log of real wages. The results of the underlying OLS estimates are reported in Table 9 in the Appendix. The estimated coefficients show minor differences concerning the regional types. Hence, we find first evidence that the returns on the characteristics under consideration seem to be not too different with respect to the regional type. The estimates provide the basis for the OBD.

Table 6: Results of the OBD: overall decomposition

Overall evaluation	**Baseline model without CHK effects**		**Augmented model including CHK effects**	
	Central-peripheral (1)	**Highly central-peripheral (2)**	**Central-peripheral (3)**	**Highly central-peripheral (4)**
Real wage comparison group	104.087***	108.597***	104.087***	108.597***
	(0.587)	(0.372)	(0.632)	(0.373)
Real wage in rural region	96.840***	96.840***	96.840***	96.840***
	(0.326)	(0.326)	(0.353)	(0.353)
Difference	1.069***	1.111***	1.075***	1.121***
	(0.007)	(0.005)	(0.008)	(0.006)
Endowments	1.040***	1.096***	1.080***	1.163***
	(0.006)	(0.005)	(0.008)	(0.006)
Coefficients	1.028***	1.024***	0.996***	0.972***
	(0.002)	(0.002)	(0.001)	(0.001)
Interaction	0.999	0.990***	0.998***	0.992***
	(0.001)	(0.002)	(0.000)	(0.001)
No of individuals	1341377	1935795	1341377	1935795
No of firms (clusters for s.e.)	284361	371771	284361	371771

Note: Cluster robust s.e. at firm level in (),* .05, ** .01, *** .001

Because our focus is on the wage gap of rural regions to other regions, we solely concentrate on the differences between peripheral and either centralized or highly centralized regions. Table 6 reports the overall evaluation of the OBD. Columns 1 and 2 show the results when CHK effects are not considered, while the results provided in columns 3 and 4 include the CHK variables. Endowment, coefficient, and interaction effects are presented in Table 7 and Table 8, respectively.

The recorded values can be interpreted as follows: e.g. the value of 1.069 in column 1 of Table 6 means that the average real wage is 6.9% higher in centralized regions compared to peripheral areas. A value below 1, like 0.972 (coefficient effect in column 4 of Table 6), means that average real wages are 2.8% lower in highly centralized areas compared to peripheral regions (due to differences in coefficients). The overall evaluation shows that the real wage difference relative to peripheral regions is substantial and ranges between 6.9% (centralized regions) and 12.1% (highly centralized regions). Endowment effects outweigh coefficient effects, while interactions are of minor importance. We interpret this as an indication that the structural differences in the spatial distribution of the individual and firm characteristics are the main driver for the centralized-peripheral wage gap. In column 2, the overall pay gap between centralised and peripheral regions (column 2) is 11.1%. This is the sum of the endowment effect (9.6%), the coefficient effect (2.4%), and the (compensating) interaction effect (1%). When the CHK effects are considered (column 4), the endowment effect becomes larger, and both coefficient and interaction effect compensate the pay gap.

Table 7 provides the different endowment effects. For example, real wages increase by 0.6% if the industry structure of the peripheral regions will be adjusted to the structure of the highly centralised areas (column 2). The different occupational mix relates to a wage difference of about 1.2% and tasks and supervision responsibility of about 1.9%. Education-related differences in the distribution can explain 2.5% of the pay gap. Adjusting the experience structure leads to a "loss" in real wage differences of 0.3%. Larger firms, which benefit from internal scale effects, locate more frequently in highly centralised regions and smaller firms locate more frequently in peripheral regions. The internal scale effects can explain 1.9% of the real wage gap because larger firms pay higher wages. There are also positive effects of employment diversity within the firms. Considering the CHK measures for unobserved individual and firm heterogeneity (columns 3 and 4 of Table 6 and Table 7), the reported effects become smaller, and almost all of the real wage gap is explained by these two characteristics of the endowment effect. Hence, the CHK measures explain 14.8% (7% plus 7.8%) of the 16.3% overall endowment effect. This indicates a skewed distribution of unobserved characteristics in space, i.e. selectivity in space.

Table 7: Results of the OB decomposition: Endowment Effect (Table 6 continued)

Endowment Effect	**Baseline model without CHK effects**		**Augmented model including CHK effects**	
	Central-peripheral (1)	**Highly central-peripheral (2)**	**Central-peripheral (3)**	**Highly central-peripheral (3)**
Industry structure (IND)	1.004***	1.006***	1.001**	1.001*
	(0.002)	(0.002)	(0.001)	(0.001)
Occupational structure (OCC)	1.003***	1.012***	1.001***	1.006***
	(0.000)	(0.001)	(0.000)	(0.000)
Individual Task level of current job (TASK)	1.003***	1.019***	1.001***	1.008***

	(0.001)	(0.001)	(0.000)	(0.000)
Personal Characteristics (INDIVID)	1.002***	1.000	1.001***	1.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Educational & Vocational Attainment (EDUC)	1.005***	1.025***	0.998***	0.993***
	(0.001)	(0.001)	(0.000)	(0.000)
Individual labour market experience (EXP)	1.006***	0.997***	1.001*	0.998***
	(0.001)	(0.001)	(0.000)	(0.000)
Firm Economies of Scale (FIRM SCALE)	1.009***	1.019***	1.002***	1.004***
	(0.002)	(0.001)	(0.000)	(0.000)
Firm Diversity (FIRM DIV)	1.008***	1.015***	1.000	0.999**
	(0.001)	(0.001)	(0.000)	(0.001)
Firm CHK effects			1.043***	1.070***
			(0.003)	(0.002)
Individual CHK effects			1.030***	1.078***
			(0.003)	(0.003)

Note: Cluster robust s.e. at firm level in (),* .05, ** .01, *** .001

Table 8, finally, reports the coefficient and interaction effects. With few exceptions, the coefficient effects are relatively small, and some are negligible. Neglecting the CHK effects, especially coefficient differences in industry, experience structure, firm size, and firm diversity are pronounced. Interestingly, there is little difference in coefficients for occupations and tasks, indicating that firms evaluate rather similar within both regional types. In general, the percentage contribution of the aggregated coefficient effect is small and becomes even negative (below 1) when the CHK effects are taken into account (column 4). Exceptions are only firm scale effects (1.009) and education (1.003).

Personal characteristics, education, experience, and firm diversity compensate to a small extent in the interaction effect of the baseline model (without CHK effects). Once unobserved heterogeneity is accounted for in the centralised-peripheral comparison (column 3 of Table 8), the interaction effects become negligible, except for the individual CHK effects. When the real wage gap is larger (highly centralised-peripheral comparison), both CHK effects drive the small compensation in favour of peripheral wages. Overall, the interaction effects show only very tiny changes. Finally, the overall small contributions of the interaction effects can also be seen as evidence for a robust and quite comprehensive specification as well as for a small index problem (Ochsen 2020).

Table 8: Results of the OB decomposition: Coefficient and Interaction effect (**Table 6** ***continued)***

		Baseline model without CHK effects		**Augmented model including CHK effects**	
		Central-peripheral (1)	**Highly central-peripheral (2)**	**Central-peripheral (3)**	**Highly central-peripheral (4)**
Coefficient effect	Industry structure (IND)	0.993	0.965***	1.009*	1.003
		(0.009)	(0.008)	(0.005)	(0.005)
	Occupational structure (OCC)	0.994	0.988***	0.999	0.997
		(0.003)	(0.003)	(0.002)	(0.002)
	Individual Task level of current job (TASK)	0.998*	0.995***	0.999	0.999**
		(0.001)	(0.001)	(0.001)	(0.001)
	Personal Characteristics (INDIVID)	0.994**	1.004*	0.995***	0.996***
		(0.002)	(0.002)	(0.001)	(0.001)
	Educational & Vocational Attainment (EDUC)	0.996***	0.996***	1.000	1.003***

		(0.001)	(0.001)	(0.001)	(0.000)
	Individual labour market experience (EXP)	1.004	1.020***	1.001	1.004
		(0.005)	(0.005)	(0.003)	(0.003)
	Firm Economies of Scale (FIRM SCALE)	1.005	1.018***	1.004**	1.009***
		(0.003)	(0.003)	(0.002)	(0.002)
	Firm Diversity (FIRM DIV)	0.994	0.969***	0.994	0.981***
		(0.007)	(0.006)	(0.003)	(0.003)
	Firm CHK effects			1.000	1.001***
				(0.000)	(0.000)
	Individual CHK effects			1.001***	1.003***
				(0.000)	(0.000)
	Constant	1.053***	1.079***	0.993	0.976***
		(0.013)	(0.013)	(0.008)	(0.007)
interaction effect	Industry structure (IND)	1.001	0.999	1.000	1.000
		(0.001)	(0.001)	(0.000)	(0.001)
	Occupational structure (OCC)	1.000	1.001	1.000	1.000
		(0.000)	(0.001)	(0.000)	(0.000)
	Individual Task level of current job (TASK)	1.000	1.000	1.000	1.001***
		(0.000)	(0.000)	(0.000)	(0.000)
	Personal Characteristics (INDIVID)	1.000	0.998***	1.000	1.000*
		(0.000)	(0.000)	(0.000)	(0.000)
	Educational & Vocational Attainment (EDUC)	0.999***	0.998***	1.000	1.003***
		(0.000)	(0.001)	(0.000)	(0.000)
	Individual labour market experience (EXP)	1.000**	0.998***	1.000	1.000
		(0.000)	(0.000)	(0.000)	(0.000)
	Firm Economies of Scale (FIRM SCALE)	1.000	1.000	1.000	1.001**
		(0.000)	(0.001)	(0.000)	(0.000)
	Firm Diversity (FIRM DIV)	1.000	0.994***	1.000	0.997***
		(0.000)	(0.001)	(0.000)	(0.001)
	Firm CHK effects			1.000	0.998***
				(0.000)	(0.001)
	Individual CHK effects			0.999***	0.993***
				(0.000)	(0.000)

Note: Cluster robust s.e. at firm level in (),* .05, ** .01, *** .001

To summarize our findings, the OBD provides evidence that most of the centralised-peripheral wage gap is explained by differences in individual and firm characteristics (endowments). For the larger highly centralised-peripheral wage gap, the differences in individual characteristics are even larger. Better skilled and better-performing individuals are located in highly centralised regions, but also the firm size and worker heterogeneity differ and are important drivers of the wage gap (Table 6, column 2). Both comparisons provide similar differences in coefficients, mainly driven by worker experience and firm size. However, once unobserved firm and individual heterogeneity are taken into account (CHK effects), the wage gaps are almost completely explained by endowments (Table 6, columns 3 & 4). However, most effects due to differences in endowments between the regional types are cut down by half or disappear because these variables now capture the deviation from the mean of the measured firm and individual heterogeneity. Moreover, when the CHK measures are included, the coefficient effects become mainly negligible (Table 8, column 3 & 4).

Because of the differences in endowments and the negligible coefficient and interaction effects, most of the wage gap is due to a skewed distribution of (un)observed characteristics in the regional types. We conclude that the selectivity in space is the primary driver of the wage gap and not differences in returns to such characteristics.

Sensitivity Analysis[4]

The assignment of regions to the respective regional type follows a definition based on population size, and density. The results presented so far highlight the impact of accessibility and centrality because the identification required overlap in characteristics. Therefore, regions with low population density but high proximity to metropolitan areas are included in the group of highly centralised regions. Therefore, we change the classification and assign regions to the three regional types solely based on population density. However, the results are in line with our previous findings of the selectivity of individuals in space. Especially education-related variables show now higher wage increases in favour of centralised centres. Additionally, firm size effects become more pronounced. As expected, because of less overlap in observed characteristics, the coefficient effect becomes more pronounced for firm scale and firm diversity compared to highly centralised regions. The conclusion, however, remains unchanged.

Even 30 years after Germany's reunification, structural differences between East and West Germany exist. Therefore, we go more into detail and re-estimate the models considering first, the model augmented by an East-Germany-indicator and, second, separate estimations for the east and the west. Third, within each regional type, we perform the OBD and distinguish between East and West Germany. The results of all three approaches provide some additional insights into the structural weakness of East Germany, but the conclusion does not change. Thus, the assignment of regions to the regional types is not driven by an East-West-Gap.

The use of real wages is particularly of importance for individuals and their potential migration decision. However, if productivity differences due to agglomeration effects affect solely nominal wages instead of real wages, our empirical strategy will be misleading. We, therefore, estimate all models considering nominal wages. The results do not change remarkable, indicating that firms pass on their potential gains in productivity to their employees and adjust salaries for regional price variation.

6. Discussion and concluding remarks

This paper considers the centralised-peripheral wage gap in Germany in 2018. We employ administrative data provided by the German Institute for Employment Research, which enables us to take care of individual and firm-specific variables to describe differences in real wages. In the analysis, individuals located in peripheral regions are compared with those located either in centralised or in

[4] The respective tables with estimation results can be shown upon request.

highly centralised regions. This paper sheds light on the wage-setting behaviour by estimating three Mincer-wage-equations, one for each regional type. Performing a threefold Oaxaca-Blinder decomposition enables us to explain the wage gap by an unequal distribution of characteristics in space (regional type differences in endowments) and unequal returns to characteristics under consideration (differences in coefficients). Even more, we uncover determinants that lead to the wage gap: Is it due to a different distribution of individuals and/or firm characteristics in space? Or is it due to the different wage-setting behaviour of firms in peripheral and (highly) centralised regions?

To summarize our findings, the observed characteristics of the individual and firm-level explain the differences in real wages between the regional types. We find no substantive effects of different wage-setting behaviour in the regional context, and thus, there are no substantial differences in returns to specific characteristics at the individual and firm-level. The CHK measures that consider the unobserved firm and individual heterogeneity turn out to be very strong predictors of endowment differences in the three regional types. We conclude that the selectivity of workers and firms in space explains the real wage gap between peripheral and (highly) centralised regions.

In reflection of theoretical literature, such differences are a result of an endogenous selection process. The findings are not solely relevant for Germany and could be transmitted to other countries with rather similar economy-specific regulations. Therefore, from a policy perspective, active (labour market) policy programmes and infrastructure investments that enable firms located in rural regions to benefit from some agglomeration effects (e.g. knowledge) could strengthen the competitiveness and education of workers and firms. This might lead to higher real wages, providing incentives to firms to raise their wages and thus, making rural regions more attractive in Germany but also worldwide.

References

Acemoglu, D.; M. Dell (2010): Productivity Differences between and within Countries. *American Economic Journal: Macroeconomics*, 2 (1):169-88. DOI: 10.1257/mac.2.1.169

Autor, D., Katz, L., & Kearney, M. (2006): The Polarization of the U.S. Labor Market. *American Economic Review*, 96(2), 189-194.

Baldwin, R.E., Forslid, R., Martin, P., Ottaviano, G. and Robert-Nicoud, F., 2004. *Economic Geography and Public Policy*. Princeton: Princeton University Press.

Blinder, Alan S. (1973): Wage Discrimination: Reduced Form and Structural Estimates. *The Journal of Human Resources*, 8 (4), 436-455.

Brunow, S.; U. Blien (2014): Effects of cultural diversity on individual establishments. *International Journal of Manpower*, 35 (1).

Brunow, S.; U. Blien (2015): Agglomeration effects on labor productivity: An assessment with microdata. *REGION*, 2 (1), 33-53.

Brunow, S.; O. Jost (2021): Wages of migrant and native employees in Germany: new light on an old issue. *International Migration Review*, forthcoming.

Brunow, S.; O. Jost (2020): Foreign Vs. German Wage Differentials in Germany: Does the Home Country Matter? In W. Cochrane, M.P. Cameron and O. Alimi (eds.) *Labor Markets, Migration, and Mobility*. Singapur, Springer, 55-76.

Brunow, S.; P. Nijkamp (2019): Firm formation and industrial agglomeration under monopolistic completion – a study on German regions. *Romanian Journal of Regional Science* 13 (2), 1-25.

Card, D.; J. Heining; P. Kline (2013): Workplace heterogeneity and the rise of West German wage inequality. *The Quarterly Journal of Economics*, 128 (3):967-1015.

Combes, P.-P., Magnac, T. and Robin, J.-M. (2004): The dynamics of local employment in France. J*ournal of Urban Economics* 56, 217-243.

Dauth, W. (2014): Job polarization on local labor markets. *IAB-Discussion Paper*, 18, 1-16

Dostie B., Li J., Card D., Parent D. (2020): Employer Policies and the Immigrant-Native Earnings Gap. National Bureau of Economic Research Working Paper Series;No. 27096.

Duranton, G.; D. Puga (2020): The Economics of Urban Density. *Journal of Economic Perspectives* 34(3), 3-26.

Roca, J.D.L., D. Puga (2017): Learning by working in big cities. *The Review of Economic Studies,* 84:1, 106-182.

Ellguth, P.; S. Kohaut (2019): A note on the decline of collective bargaining coverage * the role of structural change. *Journal of Economics and Statistics* 239:1, 39-66.

Glaeser, E.L.; H.D. Kallal; J.A. Scheinkman; A. Shleifer (1992): Growth in cities. *Journal of Political Economy*, 100(6), 1126-1152.

Glaeser E.L.; A.M. Giacomo; P. Tobio; K. Tobio (2014): Cities, Skills and Regional Change, *Regional Studies*, 48(1), 7-43.

Goos, M; A. Manning; A. Salomons (2009): Job Polarization in Europe. *American Economic Review: Papers& Proceedings* 99(2), 58-63.

Grossman, G.M.; E. Helpman (1991): Innovation and Growth in the Global Economy, MIT Press,

Haltiwanger, J.C.; J.I. Lane; J.R. Speltzer (1991): Productivity Differences Across Employers: The Roles of Employer Size, Age, and Human Capital, American Economic Review 89 (2), 94-98.

Hamann, S., Niebuhr, A., & Peters, J. C. (2019). Does the urban wage premium differ by pre-employment status? *Regional Studies*, 53:10, 1435-1446.

Henderson, J. V., Shalizi, Z., Venables, A. J. (2001) Geography and development. *Journal of Economic Geography*, 1: 81–105.

Fuchs, M.; A. Rossen; A. Weyh; G. Wydra-Somaggio (2021): Where do women earn more than men? Explaining regional differences in the gender pay gap. *Journal of regional science*, online first, 1-23.

Hirsch, B,; König, M. Möller, J. (2013): Is there a gap in the gap? Regional differences in the gender pay-gap. *Scottish Journal of Political Economy*, 60:4, 412-439.

Hoogstra G.J., van Dijk J., Florax R.J.G.M. (2017): Do jobs follow people or people follow jobs? A meta-analysis of Carlino–Mills studies. *Spatial Economic Analysis*, 12:4, 1-22.

Jann, B. (2008). The Blinder–Oaxaca Decomposition for Linear Regression Models. *The Stata Journal*, 8(4), 453–479.

Krugman, P. (1991): Increasing returns and economic geography. *Journal of Political Economy* 99, 483-499.

List, F. (1838). Das deutsche National-Transport-System in volks- und staatswirtschaftlicher Beziehung [The German national transportation system in relation with the national economy]. Altona and Leipzig: Johann Friedrich Hammerich.

Marshall, A. (1890). Principles of economics. London: Macmillan.

Niebuhr, A.; J.C. Peters (2020): Population diversity and regional economic growth. In: M. M. Fischer & P. Nijkamp (ed.), *Handbook of regional science*, Berlin: Springer, 17p.

Niebuhr, A. ; J.C. Peters; A. Schmidke (2019): Spatial sorting of innovative firms and heterogeneous effects of agglomeration on innovation in Germany. *The journal of technology transfer*, online first, 1-33.

Oaxaca, R. (1973): Male-Female Wage Differentials in Urban Labor Markets. International Economic Review, 14 (3), 693-709.

Ochsen, C. (2020): Interaction Effect in Wage Decomposition, mimeo.

Rice, P., Venables, A. J., Patacchini, E. (2006) Spatial determinants of productivity: analysis for the regions of Great Britain. *Regional Science and Urban Economics* 36, 727–752.

Rokicki, B.; U. Blien; G.J.D. Hewings; Phan thi H. Van (2021): Is there a Wage Curve with Regional Real Wages?, *Economic Modelling* (102), article 105582.

Roscher, W. (1878). Ansichten der Volkswirtschaft aus dem geschichtlichen Standpunkte [Notion of the national economy from a historical perspective], Vol. 2. Leipzig and Heidelberg: C. F. Wintersche Verlagshandlung.

Rosenthal S, Strange W (2004) Evidence on the nature and sources of agglomeration economies. In: Henderson J, Thisse J (eds): *Handbook of Regional and Urban Economics*. Elsevier, Amsterdam

Saito, H.; M Gopinath (2009): Plants' self-selection, agglomeration economies and regional productivity in Chile. Journal of Economic Geography 9(4), 539-558.

Trax, M., S. Brunow, J. Südekum (2015): Cultural diversity and plant level productivity. *Regional Science and Urban Economics*, 53, 85-96.

Weinand, S.; L. von Auer (2020): Anatomy of regional price differentials: evidence from micro-price data, *Spatial Economic Analysis,15(4), 413-440*, DOI: 10.1080/17421772.2020.1729998.

Appendix

Table 9: OLS estimates of the augmented wage equation

	Baseline model without CHK effects				Augmented model including CHK effects			
	Pooled	Highly centralized	centralized	peripheral	Pooled	Highly centralized	centralized	peripheral
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Individual characteristics								
Unskilled Tasks	-0.097***	-0.108***	-0.092***	-0.087***	-0.035***	-0.041***	-0.032***	-0.028***
	(0.002)	(0.003)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Specialist/Expert	0.149***	0.151***	0.146***	0.149***	0.066***	0.069***	0.064***	0.064***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Supervisor responsibility	0.031***	0.024***	0.040***	0.039***	0.023***	0.019***	0.027***	0.026***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.003)
Executive responsibility	0.174***	0.161***	0.184***	0.196***	0.065***	0.062***	0.067***	0.071***
	(0.002)	(0.003)	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.003)
Age: 16 to 24 years	-0.075***	-0.093***	-0.071***	-0.054***	-0.145***	-0.160***	-0.141***	-0.120***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.002)	(0.003)	(0.003)	(0.003)
Age: 25 to 34 years	-0.011***	-0.012***	-0.008***	-0.011***	-0.060***	-0.061***	-0.060***	-0.057***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
Age: 45 to 54 years	0.013***	0.015***	0.008***	0.010***	0.000	0.001	-0.001	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Age: 55+ years	-0.016***	-0.009***	-0.024***	-0.030***	-0.060***	-0.057***	-0.063***	-0.064***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Gender (female=1)	-0.139***	-0.130***	-0.155***	-0.140***	-0.067***	-0.067***	-0.071***	-0.060***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Foreigner (=1)	0.013***	0.005***	0.020***	0.026***	0.008***	0.007***	0.010***	0.010***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)

***Table 9:* OLS estimates of the augmented wage equation (continued)**

	Baseline model without CHK effects				**Augmented model including CHK effects**			
	Pooled	**Highly centralized**	**centralized**	**peripheral**	**Pooled**	**Highly centralized**	**centralized**	**peripheral**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
No school degree	-0.027***	-0.022***	-0.037***	-0.023***	-0.013***	-0.009***	-0.021***	-0.014***
	(0.003)	(0.005)	(0.005)	(0.005)	(0.002)	(0.003)	(0.004)	(0.004)
Upper secondary educ. (Abitur)	0.053***	0.055***	0.050***	0.049***	-0.020***	-0.015***	-0.026***	-0.027***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
No vocational training	-0.059***	-0.065***	-0.057***	-0.041***	-0.020***	-0.020***	-0.023***	-0.017***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
University degree	0.163***	0.158***	0.167***	0.181***	-0.013***	-0.009***	-0.018***	-0.019***
	(0.002)	(0.002)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
Foreman	0.080***	0.078***	0.083***	0.083***	-0.038***	-0.037***	-0.038***	-0.042***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Log mean duration	0.077***	0.081***	0.071***	0.072***	0.011***	0.015***	0.007***	0.005***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log firm duration	0.026***	0.025***	0.028***	0.025***	0.015***	0.014***	0.017***	0.017***
	(0.000)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)
LM experience (2^{nd} Quartile)	0.042***	0.051***	0.032***	0.024***	0.064***	0.065***	0.062***	0.065***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)
LM experience (3^{rd} Quartile)	0.046***	0.054***	0.041***	0.032***	0.065***	0.063***	0.066***	0.070***
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.002)	(0.002)	(0.003)
LM experience (4^{th} Quartile)	0.016***	0.025***	0.014***	0.001	0.027***	0.027***	0.027***	0.028***
	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.003)	(0.003)
No. of firms	0.006***	0.006***	0.006***	0.007***	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

Table 9: OLS estimates of the augmented wage equation (continued)

	Baseline model without CHK effects				Augmented model including CHK effects			
	Pooled (1)	**Highly centr. (2)**	**centralized (3)**	**peripheral (4)**	**Pooled (5)**	**Highly centr. (6)**	**centralized (7)**	**peripheral (8)**
Non-employment 5% to <10%	-0.074***	-0.071***	-0.072***	-0.076***	-0.014***	-0.015***	-0.012***	-0.013***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Non-employment 10% to <25%	-0.116***	-0.114***	-0.114***	-0.118***	-0.023***	-0.025***	-0.018***	-0.020***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)
Non-employment 25% to <75%	-0.167***	-0.161***	-0.164***	-0.172***	-0.034***	-0.038***	-0.031***	-0.025***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
Firm characteristics								
Firm size: 10 to <50 employees	0.097***	0.108***	0.093***	0.082***	0.020***	0.024***	0.019***	0.015***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Firm size: 50 to <250 employees	0.145***	0.159***	0.136***	0.128***	0.030***	0.035***	0.029***	0.024***
	(0.001)	(0.002)	(0.002)	(0.003)	(0.001)	(0.001)	(0.002)	(0.002)
Firm size: 250 employees and more	0.232***	0.240***	0.232***	0.229***	0.051***	0.056***	0.051***	0.044***
	(0.002)	(0.003)	(0.004)	(0.005)	(0.001)	(0.002)	(0.002)	(0.003)
Share females in firm	-0.133***	-0.115***	-0.152***	-0.154***	-0.028***	-0.032***	-0.026***	-0.025***
	(0.003)	(0.004)	(0.005)	(0.006)	(0.002)	(0.003)	(0.003)	(0.003)
Share foreigners: >0% to <5%	0.032***	0.037***	0.030***	0.023***	0.004***	0.006***	0.001	0.002
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)	(0.002)
Share foreigners: 5% to <10%	0.057***	0.051***	0.063***	0.054***	0.004***	0.003**	0.004**	0.004*
	(0.002)	(0.003)	(0.003)	(0.004)	(0.001)	(0.002)	(0.002)	(0.002)
Share foreigners: 10% to <15%	0.049***	0.041***	0.055***	0.046***	-0.003*	-0.007***	-0.001	0.002
	(0.002)	(0.003)	(0.004)	(0.005)	(0.001)	(0.002)	(0.002)	(0.003)
Share foreigners: 15% to <20%	0.039***	0.033***	0.042***	0.041***	-0.005***	-0.008***	-0.006***	0.001
	(0.003)	(0.004)	(0.004)	(0.006)	(0.001)	(0.002)	(0.002)	(0.003)
Share foreigners: 20% to <30%	0.028***	0.021***	0.024***	0.050***	-0.013***	-0.019***	-0.012***	0.003
	(0.003)	(0.003)	(0.004)	(0.007)	(0.001)	(0.002)	(0.002)	(0.003)
Share foreigners: 30% to <50%	0.010***	0.002	0.016***	0.027***	-0.013***	-0.021***	-0.007***	0.001
	(0.003)	(0.004)	(0.004)	(0.005)	(0.002)	(0.002)	(0.002)	(0.003)

Table 9: OLS estimates of the augmented wage equation (continued)

	Baseline model without CHK effects				Augmented model including CHK effects			
	Pooled	Highly centralized	centralized	peripheral	Pooled	Highly centralized	centralized	peripheral
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Share foreigners: 50% to <75%	-0.016***	-0.027***	0.005	-0.008	-0.020***	-0.028***	-0.009**	-0.013***
	(0.004)	(0.005)	(0.007)	(0.007)	(0.002)	(0.003)	(0.004)	(0.005)
Share foreigners: 75% to 100%	-0.083***	-0.095***	-0.056***	-0.068***	-0.035***	-0.043***	-0.025***	-0.028***
	(0.004)	(0.005)	(0.007)	(0.012)	(0.003)	(0.004)	(0.005)	(0.007)
Share young workers (<35 years)	-0.045***	-0.082***	-0.006	0.026***	-0.003	-0.015***	0.005	0.016***
	(0.005)	(0.009)	(0.006)	(0.008)	(0.002)	(0.004)	(0.004)	(0.004)
Share older workers (55+ years)	-0.123***	-0.133***	-0.111***	-0.108***	-0.040***	-0.054***	-0.030***	-0.026***
	(0.004)	(0.006)	(0.007)	(0.008)	(0.003)	(0.004)	(0.005)	(0.005)
Share complex tasks	0.068***	0.067***	0.070***	0.061***	-0.014***	-0.015***	-0.013***	-0.014***
	(0.004)	(0.005)	(0.006)	(0.007)	(0.002)	(0.003)	(0.003)	(0.004)
CHK Firm effects					0.172***	0.169***	0.174***	0.175***
					(0.001)	(0.001)	(0.001)	(0.001)
CHK Individual effects					0.251***	0.242***	0.257***	0.266***
					(0.001)	(0.001)	(0.001)	(0.001)
Constant	-0.315***	-0.302***	-0.324***	-0.366***	0.016***	0.020***	0.038***	0.045***
	(0.005)	(0.008)	(0.007)	(0.009)	(0.003)	(0.005)	(0.005)	(0.006)
Heterogeneity:	Industry and occupation fixed effects included in each model							
Regional type FE	yes	no	no	no	yes	no	no	no
No of individuals	3108207	1584672	916044	607491	2742398	1401021	806603	534774
Adjusted R2	0.537	0.543	0.538	0.516	0.712	0.708	0.712	0.713
No of firms (for clustered s.e.)	629961	296322	192263	141376	535660	251299	163889	120472

Note: Cluster robust s.e. at firm level in (),* .05, ** .01, *** .001