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MIGRATION AND WAGE INEQUALITY: A DETAILED ANALYSIS FOR GERMAN REGIONS OVER TIME

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Migration and Wage Inequality: A Detailed Analysis for German Regions over Time*

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Abstract

This study presents new evidence on immigrant-native wage differentials estimated in consideration of regional differences regarding the presence of Non-German population in metropolitan and non-metropolitan areas between 2000 and 2019 in Germany. Using linked employer-employee-data, unconditional quantile regression models are estimated in order to assess the degree of labor market integration of foreign workers. Applying an extended version of the Oaxaca-Blinder decomposition method, the results provide evidence on driving factors behind wage gaps along the entire wage distribution. There are not only changes in the relative importance of explanatory factors over time, but also possible sources of wage differentials shift between different points of the wage distribution. Differentiating between various areas in Germany, on average, larger wage gaps are revealed in metropolitan areas with at the same time a higher presence of the foreign population. Regarding the size of overall estimated wage gaps, after 2012 a reversal in trend and particular increasing tendencies around median wages are identified.

JEL classification: J15 J31 J61 R23 R58
Keywords: Immigrant-native wage gap, Oaxaca-Blinder decomposition, unconditional quantile regression, ethnic clustering, Germany

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1 Introduction

The extent of wage differentials between native and foreign workers provides insights on how well immigrants are integrated in the German labor market. Detailed analyses of characteristics and developments of wage gaps over time are thus of great importance for decisions in immigration and labor market policies. With regard to migration movements during the last years, profound research in this crucial labor market issue plays an important role, especially for Germany (Ingwersen and Thomsen 2021; Brunow and Jost 2019).

This paper adds to current literature evidence on developments of wage differentials between German and Non-German workers with a special focus on possible effects resulting from changes in the share of foreign population. In particular, the extent of wage gaps is estimated in consideration of regional differences regarding the presence of Non-German population due to ethnic clustering in German metropolitan areas. It further contributes not only new findings for the years after the beginning of the refugee crisis in 2014/15, but also reveals estimation results for several points in time and how the impact of various explanatory factors on wage differentials evolves over time.

Using administrative linked-employer-employee data provided by the Research Data Center of the German Institute for Employment Research (IAB) full-time employed workers according to their nationality are subject of analyses from 2000 to 2019. Considering a rich set of individual-, firm- and regional-specific explanatory factors, this study is based on estimating unconditional partial effects in the framework of the recentered influence functions (RIF) regressions approach introduced by Firpo et al. (2018). This approach allows detailed estimations along the entire wage distribution, considering disparities away from mean wages. On the basis of this estimation strategy, aggregate and detailed decompositions are estimated applying the RIF-regressions based Oaxaca-Blinder decomposition (Fortin et al., 2011).

Descriptive analyses regarding raw wage gaps between German and Non-German workers provide evidence that there are not only significant differences in wage distributions but also growing differentials around median wages after 2012. Another important contribution of this paper is to consider regional differences regarding the presence of the foreign population in Germany. On the level of districts, tendencies of ethnic clustering in large cities and metropolitan areas are identified. At the same time, on average, higher immigrant-native wage differentials are estimated in these regions.

Applying detailed decomposition analyses, this study provides insights in the driving factors behind overall wage gaps in Germany as well as separately for metropolitan and non-metropolitan areas. There is not only evidence for changes in the relative im-

portance of specific factors over time, but also sources of possible wage disadvantages of foreign workers shift between different parts of the wage distribution. This can be seen by a shrinking relative effect due to differences in educational attainment independent of the location at the wage distribution. Further, wage gaps in the lower half of the distribution are explained to large parts by differences in the sector of employment. Despite the fact that the analysis covers only full-time working employees, it seems that there is a certain allocation to lower paid economic sectors for Non-German workers. In contrast to this, at the upper half of the distribution wage gaps mainly occur due to differences in exercised occupations. Differences in the regional presence of the foreign population mainly impact wage gaps of the lower half of the distribution. Further, regional-specific decomposition analyses in metropolitan and non-metropolitan areas contribute evidence on varying impact of characteristics explaining wage gaps.

The remainder of this paper proceeds as follows: Section 2 provides an overview on related literature. In Section 3, the used data set is described and corresponding to that, general trends in migration and regional differences in Germany as well as descriptive statistics are presented in Section 4. Further, in Section 5 the empirical approaches are specified and finally, the empirical results are presented in Section 6. Discussion and conclusion of the estimated findings are provided in Section 7.

2 Related Literature

Due to recent migration developments, studies analyzing wage differentials between immigrant and native-born workers attracted special interest during the last years. Lehmer and Ludsteck (2011) cover the time span from 1995 to 2006 and analyze wage differentials of workers from different East as well as West European countries compared to German workers. On the basis of the Oaxaca-Blinder decomposition and employment register data they find that overall wage differentials vary considerable between different countries of origin with at the same time significant heterogeneity within nationality groups. Further, coefficient effects ranging between 4 and 17 percent are identified, that indicate „pure wage discrimination“. Using matched employer-employee data Bartolucci (2014) reveals wage differentials between 12.8 and 16.8 percent for 1996 to 2005 in West Germany. Ohlert et al. (2016) provide evidence on establishment specific wage differentials between immigrant and German workers between 2000 and 2010 and show that wage gaps decrease in establishments covered by collective bargaining agreements. Further, differentials are mainly attributable to the factors education and work experience. The analyses done by Aldashev et al. (2012) provide information on the immigrant-native wage gap in Germany between 1992 and 2009 based on the Ger-

man Socio-Economic Panel (SOEP) data. They reveal that educational attainment in Germany considerably reduces the unexplained effect, indicating inferior adaptability of foreign education in Germany. The recent study by Ingwersen and Thomsen (2021), also based on SOEP data, decomposes the immigrant-native wage gap using recentered influence function regressions between 1994 and 2015. During the observed time span they find significantly growing differentials with higher wages for both foreign and naturalised immigrant workers. The presented aggregate decomposition identifies effects due to differences in characteristics that amount to overall 80 percent of the estimated wage gaps. However, this endowment effect changes from 50 to almost 100 percent along the wage distribution. Therefore, estimated decompositions suggest a certain wage disadvantage for Non-German workers compared to their German counterparts. The presented literature results that the majority of studies stems from the period between the late 1990s and 2010, respectively 2015. Thus, recent developments, especially after 2015, are not subject of current research regarding wage differentials in Germany. Further, in the face of increasing migration, driving forces behind occurring wage gaps are of major importance for immigration and labor market policies. Therefore, detailed decompositions of wage gaps along the entire wage distribution in the course of time are crucial and thus presented in this study.

Besides standard explanatory factors that are considered when it comes to decomposing wage gaps, the following analyses take the regional presence of foreign population and differences due to ethnic clustering into account. First of all, literature that covers effects of immigration on labor market outcomes of the host-country's workforce imply possible consequences on wage distributions. It is argued that a rise of foreign population increases direct competition between foreign and native workers. Due to the fact that immigrants are assumed to be close substitutes for a specific part of the native workforce, wages of the latter might be exposed to downward tendencies. At the same time, the remaining group of native workers, that is seen as a complement to the prevalent type of immigrant workers, might face enhanced possibilities in remuneration and employment (Borjas, 2014). Building up on these results Ottaviano and Peri (2012) provide evidence of a small but significant degree of imperfect substitutability between native and foreign workers with comparable levels of education and work experience. Further, they show that competition takes place among the group of foreign workers and negative effects on the native workforce are reduced. In the long run, immigration to the US lead to a moderate overall average positive effect on native wages as well as to an overall average negative effect on wages of already existent immigrants. Card (2009) reports that an increase in immigrant population has no major effect on

the wage inequality of natives, however overall wage inequality would be lower without further immigration in the US. Second of all, the underlying data reveals that the share of immigrants is significantly higher in German metropolitan areas[1] as in their rural counterparts (Federal Bureau of Statistics (Destatis), 2021a). It seems that ethnic clustering plays a non-negligible role in the decision of residence for foreign born workers in Germany. The resulting consequences with respect to labor market outcomes are still debated in current literature. On the one side, it is argued that due to close social contact to other immigrants, information on the host country, the welfare system and vacant jobs, is faster and specifically communicated. Thus, ethnic clustering can be seen as enhancement of social integration and labor market participation (Bertrand et al. 2000; Beaman 2011). On the other side, there is evidence that these network effects can reduce the necessity to improve the country-specific human capital concerning language skills and educational knowledge (Warman, 2007). As a result, the pace of integration into the labor market of the host country could be reduced and labor market outcomes are affected negatively. Immigrants, living in metropolitan areas with high ethnic clustering, are further seen to be exposed to slower wage growth (Borjas, 2000). For Germany, Kanas et al. (2012) highlight the importance of social contact with co-ethnic population in ensuring employment of the foreign population but also identify limited access to high-status workplaces for immigrant workers in areas with higher levels of ethnic clustering. Winke (2018) reveals that despite higher marginal income due to more ethnic clustering, large incomes of the foreign population only increase with less. Further, moving into urban regions is accompanied with more co-ethnic neighbours for migrants whereas the opposite is shown for Germans. Schaffner and Treude (2014) present negative effects on wages and employment for immigrants resulting from ethnic clustering in large cities in Germany. It is concluded that these observations could be one determinant why foreign workers persistently earn less than their German counterparts. Motivated by these findings, the decomposition analyses are additionally estimated separately for metropolitan and non-metropolitan areas in Germany, where the explanatory factors control for the composition of the workforce in different regions.

3 Data

The German linked employer-employee data (LIAB), provided by the Research Data Center of the Institute for Employment Research (IAB), summarizes information on the

[1]The metropolitan areas are based on the definition of the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022). For more details, see Section 4.

yearly representative employer survey (IAB Establishment Panel) with corresponding establishment and individual data, drawn from labor administration and social security.[2] The reference date of LIAB data is June 30th in each year, where information on establishments is matched with social security data of workers that were employed in those establishments at this day. Therefore, the panel does not consider workers that do not contribute to social security. Further, LIAB data provide a wide set of characteristics of observed individuals and of the particular establishment in which they are employed. The data set contains individual information on workers such as gender, year of birth, vocational training, education and place of residence as well as information on their employment such as daily wage, occupation, number of days in employment and job. In addition, the data set provides details on the classification of economic activities, total number of employees and region of activity of establishments. In order to ensure a representative sample, this study takes sample weights, provided by the IAB, into account.

The main variable identifying German or Non-German workers is defined on the basis of citizenship. As a result, the study covers mainly first-generation migrants, since second-generation migrants more likely accept the German citizenship. Due to this data design, workers that are identified as Non-Germans more likely obtained their school-leaving qualification abroad and exhibit differences regarding their human capital endowments compared to Germans. Further, possible language barriers and thus effects resulting from the unexplained part of the wage gap can be identified as well. Since the analysis is restricted to full-time workers, it is also assumed that the observed Non-German workers are potentially well-integrated into the German labor market and do not represent marginalized groups forced to work in certain sectors or conduct particular occupational tasks. Further studies with similar design and reasoning regarding the definition of the main variable are, for example, Brunow and Jost (2019) and Ohlert et al. (2016).

The empirical analysis considers male workers between 25 and 55 years[3], who earned more than 10 Euros per day between 2000 and 2019. At the upper end, the underlying data on wage earnings is right-censored at the contribution assessment ceiling of the social security system. In order to circumvent this issue, the wage imputation

[2]In more detail, this study uses the Linked-Employer-Employee-Data (LIAB) of the Institute for Employment Research (IAB): LIAB cross-sectional model 2 1993-2019, version 1. Research Data Centre of the Federal Employment Agency (BA) at the IAB. DOI: 10.5164/IAB.LIABQM29319.de.en.v1. The data access was provided via on-site use at the Research Data Centre (FDZ) of the German Federal Employment Agency at the Institute for Employment Research and subsequently remote data access. For detailed data description see Ruf et al. (2021).

[3]The selection of workers according to their age follows the reasoning of Ingwersen and Thomsen (2021). It is argued that there is a different participation in public education for young and varying ages of retirement of older individuals depending on their nationality.

method following the approach by Gartner (2005) is applied. Using this method in order to impute wages, yearly tobit estimations above the social security threshold are estimated controlling for standard factors such as age, education, tenure, occupational field and nationality. Using the Consumer Price Index provided by the German Federal Statistical Office non-censored and imputed wages are converted into constant 2015 Euros.

Following recent literature on wage differentials between German and foreign workers, the analysis considers data on West Germany. The decision of excluding East Germany stems from the still present significantly different labor market and wage setting processes. Further, a separate analysis is not intended due to the smaller presence of Non-German workers in the East German sample and the resulting not representative estimations (see Aldashev et al. 2012 and Ohlert et al. 2016). For the same reasons, it is unfortunately not possible to consider female workers in the underlying analyses due to the not sufficient extent of observations on German and especially Non-German women on the district level.

Furthermore, the decomposition analyses consider possible effects due to the presence of foreign population on a regional level. The required data set is provided by the German Federal Office of Statistics at the district level (Federal Bureau of Statistics (Destatis), 2021a).[4] Thus, it is possible to match this data set with the administrative labor market data using the variable indicating the district of employment.[5] Due to restrictions of data availability on a yearly and district-level basis, the regional data is aggregated at the level of German spatial planning regions, „Raumordnungsregionen“ (ROR).[6] This aggregation summarizes districts defined by the NUTS (Nomenclature of Territorial Units for Statistics) classifications that belong to a specific economic center and its surrounding areas. As a result of this, possible interrelations of commuters are considered and analyses on inter-regional disparities on labor market outcomes can be conducted (BBSR Bonn, 2019).[7]

[4]Between 2000 and 2019 there are several changes in the composition of districts. The major changes are listed in Table in A.1 in Appendix A. The respective merged districts are considered as one district over the whole period of observation.

[5]Due to its particular sensitivity with regard to data protection legislation, this variable is only available on application, see Ruf et al. (2021).

[6]The German spatial planning regions are called ROR-regions thereafter.

[7]A detailed graphical depiction of the defined ROR-regions with their respective districts is provided by the BBSR Bonn (2019).

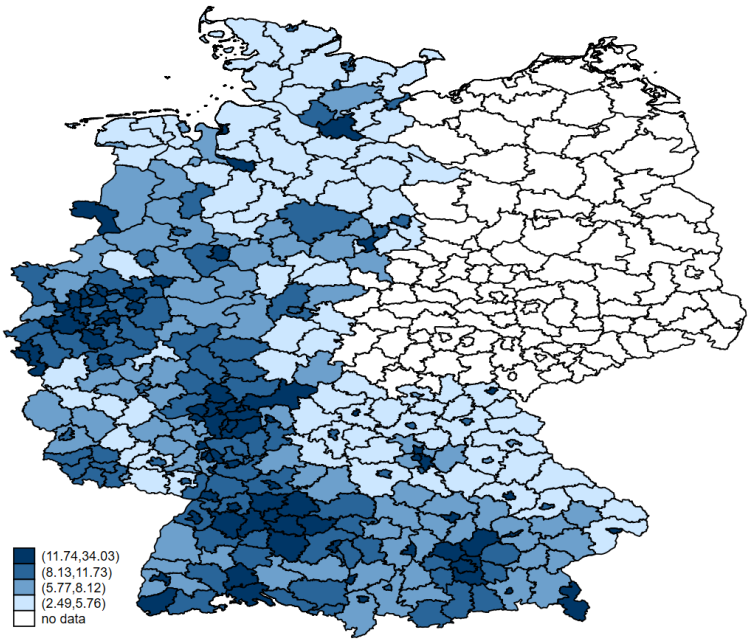
4 Descriptive Evidence

This section presents information on the foreign population in Germany and related regional differences. Further, it gives a first impression of wage differentials between German and Non-German workers as well as their development over time and provides descriptive statistics regarding the observed characteristics.

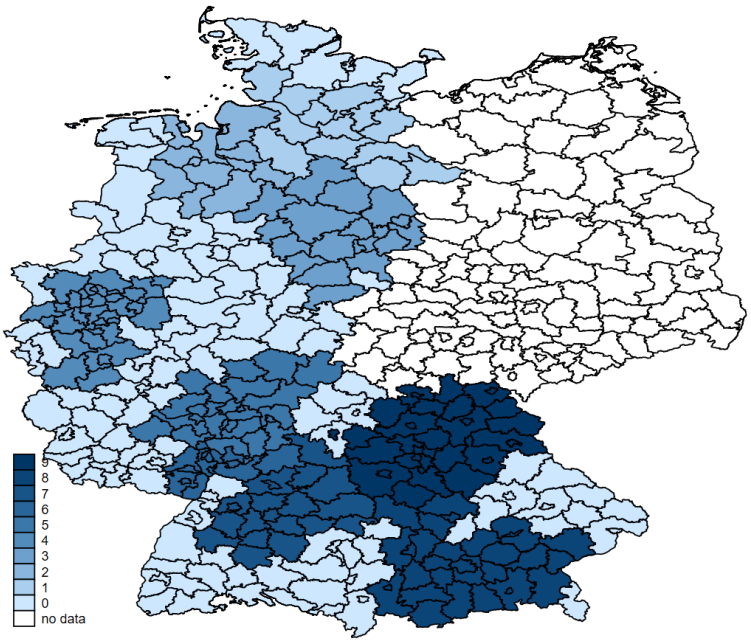
Immigration and regional differences. Due to several migration flows after the Second World War, Germany exhibits today a society with several nations and cultures of different regions from all over the world. Starting with the targeted recruitment of the so-called guest-workers in the 1950s, workers from Turkey and southern Europe dominated immigration in West Germany. The subsequent developments regarding family reunifications and the downfall of the Iron Curtain, which increased migration of Eastern European countries, lead to further changes in the foreign workforce (Dorn and Zweimueller, 2021). During the last 10 years Germany experienced major changes in the composition of the foreign population. Whereas the fraction of foreign born individuals was more or less constant since 1996 (around 8%), the immigrant share increased by 5 percentage points to 12,12% in 2019 (Federal Bureau of Statistics (Destatis), 2021a). Of course, this development is referable to the significant inflow of migrants coming from Eastern Europe and the begin of the refugee crisis in 2014/15. The largest groups of immigrants today originate from Turkey, Poland, Italy, countries of former Yugoslavia and other eastern European countries. Nonetheless, there is also a growing fraction of foreign born population coming from countries of the Middle East and Asia, such as Syria, Afghanistan and Iraq (Federal Bureau of Statistics (Destatis), 2021b).

Having a closer look at the regional settlement of the foreign population in West-Germany, Figure 1 (a) provides evidence of a specific pattern. The figure presents the share of Non-Germans on the level of administrative districts, where a darker color reflects a higher value. Thus, regions with concentrated higher numbers of foreign population are revealed. Figure 1 (b) presents metropolitan regions of West Germany defined by the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022) in 2008 (Wacker, 2016).[8] The concept of European Metropolitan Regions was introduced in the mid-1990s as a program of social,

[8] In total, there are 11 metropolitan areas in Germany (Initiative Circle European Metropolitan Regions in Germany (IKM), 2022). Due to the study design, the two regions in East Germany (Capital Region Berlin/Brandenburg and Central Germany) are not considered in the following.



(a) Share of the foreign population in West Germany, 2000-2019



(b) Metropolitan areas in West Germany

Figure 1: Regional differences

Source: (a) Federal Bureau of Statistics (Destatis) (2021a), (b) Wacker (2016), own depiction.
Note: Figure (a) presents the share of the foreign population at the level of administrative districts in West Germany for 2000 to 2019. Figure (b) presents metropolitan areas in West Germany defined by the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022), where (1): metropolitan area Hamburg, (2): metropolitan area Northeast, (3): metropolitan area Hannover Braunschweig Göttingen Wolfsburg, (4): metropolitan area Rhine-Ruhr, (5): metropolitan area Frankfurt Rhine-Main, (6): metropolitan area Rhine-Neckar, (7): metropolitan area Stuttgart, (8): metropolitan area Munich, (9): metropolitan area Nuremberg and (0): West-German non-metropolitan area.

economical and cultural advancement aiming to support the international performance and competitiveness of Germany.[9] Comparing these areas with the observed ethnic clusters of Figure 1 (a), it is shown that migrants tend to settle down in larger cities and economically prospering regions.[10] Especially, the areas Rhine-Ruhr, Frankfurt Rhine-Main, Stuttgart and Munich reveal a high level of this relationship. From this, one can conclude that ethnic clustering is an observable factor in Germany that should be examined further, especially with a view to possible impacts on labor market outcomes of German and Non-German workers.

Wage distributions and raw wage gaps. In order to show wage differentials between German and Non-German workers along the entire wage distribution, Figure 2 presents kernel density estimations considering the whole period of observation from 2000 to 2019. For the first half of the distributions, the density of German workers is at any point lower than that of Non-German workers implying substantial differences. The two densities cross at the log wage level of 4.6 and show that more German workers are present in the upper half of the wage distribution. In total, a shift to the left for Non-German workers compared to German workers and thus a substantial wage gap at any point to the detriment of the former is revealed.

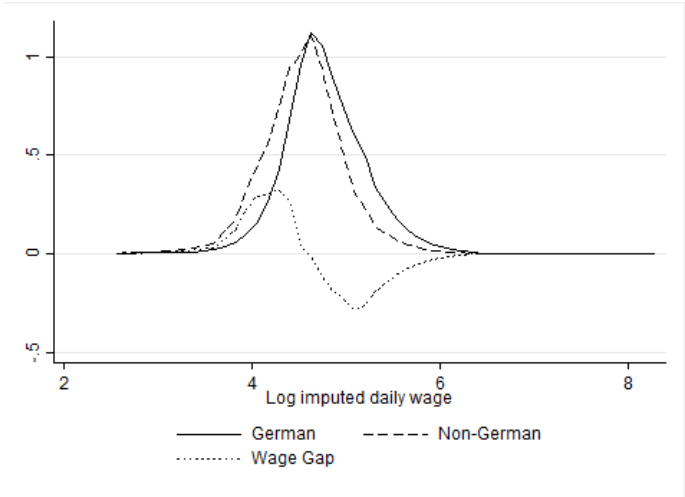


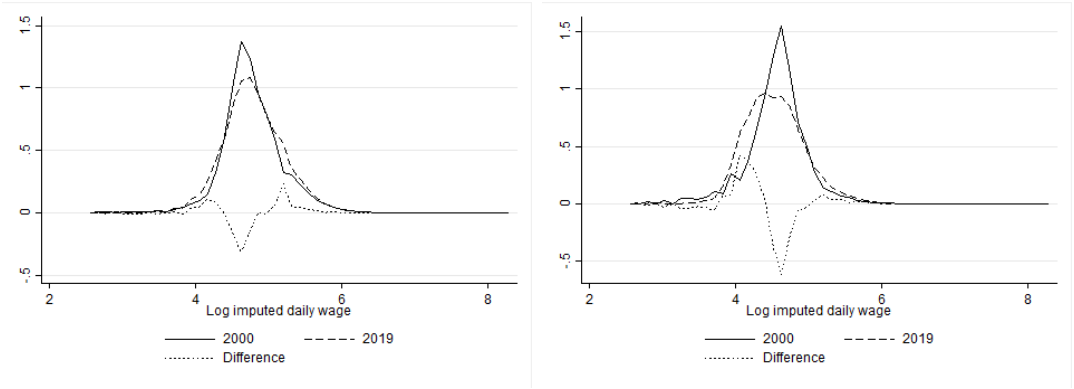
Figure 2: Wage densities by nationality, 2000-2019

Source: LIAB QM2 9319, own calculations.
Note: The figure presents kernel density estimations of the wage densities for German and Non-German workers between 2000 and 2019. Sampling weights are employed.

Since this study seeks in providing evidence on changes in wage differentials over time, Figure 3 shows the wage densities separated by nationality for the years 2000 and

[9]For further details see Michel (1998), Rusche and Oberst (2010) and Diller and Eichhorn (2022).
[10]These findings are in line with Schaffner and Treude (2014), Glitz (2014) and Winke (2018).

2019 and its corresponding difference. Comparing both time points, in both subfigures a significant drop of the density in the middle of the distribution and resulting increased wage dispersions are observable. This trend is especially observable for wages of foreign workers. Further, when it comes to the reallocation of wages along the distribution, an opposite trend depending on nationality is identified. On the one side, in subfigure (a) more mass is sifted to the right of the distribution, indicating an increase of German workers in higher paid jobs. On the other side, subfigure (b) shows for Non-German workers a higher difference between 2019 and 2000 at the lower half of the distribution. Thus, substantial wage differences between German and Non-German workers that change over time and are influenced by the widening of the group's wage distributions are identified.



(a) German workers (b) Non-German workers

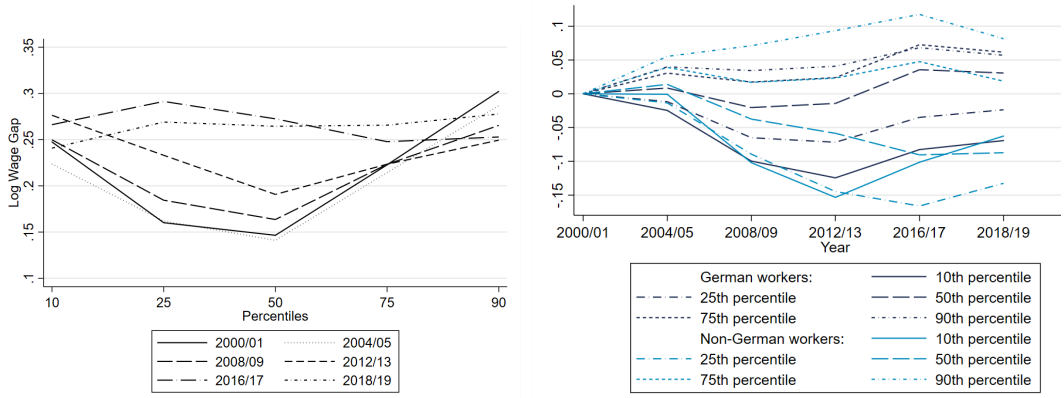
Figure 3: Wage densities over time, by nationality

Source: LIAB QM2 9319, own calculations.
Note: The figures present kernel density estimations of the wage densities for German (a) and Non-German (b) workers in comparison for the years 2000 and 2019. Sampling weights are employed.

Going into more detail how wage differentials evolve over time at different points of the wage distribution, Figure 4 (a) presents raw wage gaps between German and foreign workers for the 10th, 25th, 50th, 75th and 90th percentiles over time.[11] In general, substantial differences along the wage distribution and a distinct U-shaped form between 2000 and 2012 can be confirmed. However, after 2012 a significant trend reversal is identified, where in the middle of the wage distribution log wage gaps increase. As a result of this, the significant U-shaped form flattens over time and in 2019 there is a more or less equal value of log wage gaps along the whole wage distribution. Having a look at the respective wage growth of different wage percentiles, this development can be derived from Figure 4 (b). Until 2008 median wages stayed

[11] In the following, the analyses are based on pooled time points in order to circumvent possible outliers.

more or less constant over time, whereas afterwards a diverging development starts. Increasing German wages and at the same time decreasing Non-German wages lead to a considerable increase in the log wage gap at this point. The same developments at the end of the observed period can be seen for the 25th and 75th percentiles. Further, nameable developments are identified at the lower and upper ends. Both, German and Non-German workers are exposed to significant decreases at the 10th percentile, with a small trend reversal starting in 2012. The opposite is revealed for wages at the 90th percentile that experience major increases over the whole period, where foreign wage growth is mainly the highest. This descriptive presentation highlights once more the necessity to decompose wage differentials separately at different time points since otherwise the observed changes are overlooked.



(a) Wage gaps by percentiles, 2000-2019 (b) Wage growth by percentiles and nationality, 2000-2019

Figure 4: Wage gaps and growth over time

Source: LIAB QM2 9319, own calculations.
Note: Figure (a) presents wage gaps between German and Non-German workers by percentiles (10, 25, 50, 75, 90) between 2000 and 2019. Figure (b) presents the wage growth for German and Non-German workers for different percentiles. The base year is 2000/01. Sampling weights are employed.

Since this study seeks in providing evidence on differences between metropolitan and non-metropolitan areas, Figure 5 presents mean wage differentials at the level of ROR-regions in West Germany. Once again, regional accumulations of certain value ranges are identified. Areas with the highest observed wage gaps between German and Non-German workers noticeably correspond to the defined metropolitan areas of Figure 1 (b). Especially, the regions around Hamburg, Bremen, Frankfurt Rhine-Main, Stuttgart, Munich and Nuremberg exhibit the highest observed wage gaps. This relationship is supported by kernel density estimations in Figures B1-B3 in Appendix B, where a higher wage dispersion and a larger shift between German and Non-German

workers are presented in metropolitan regions.[12]

As a result of these findings, the following decomposition analyses are as well conducted separately for metropolitan and non-metropolitan areas.

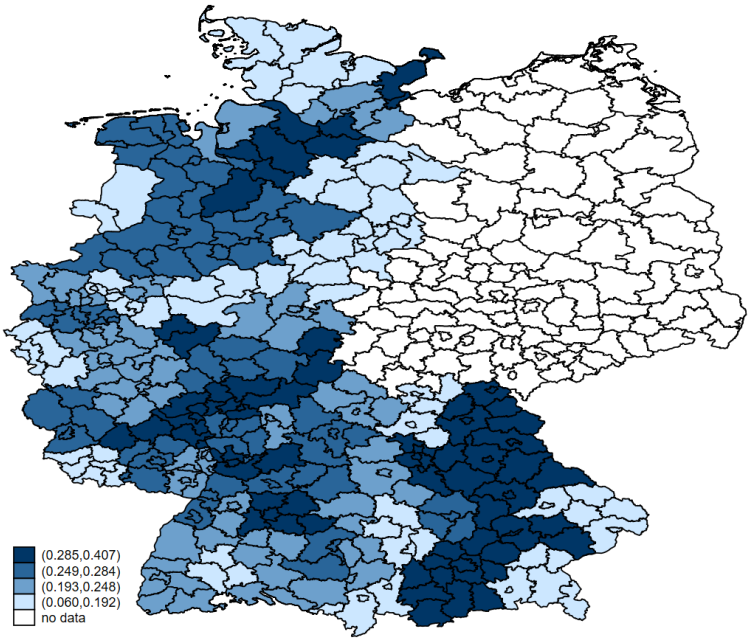


Figure 5: Wage differentials between German and Non-German workers, by regions

Source: LIAB QM2 9319, own calculations.
Note: The Figure presents the wage differentials at the mean between German and Non-German workers at the level of ROR-regions in West Germany, 2000-2019.

Who are the observed workers? A closer look at explanatory factors provides first information of possible differences in the composition of workforce. The descriptive statistics for selected variables are presented in Table 1. The first group of characteristics summarizes individual endowments of workers such as age, education, days in employment and job tenure. It is revealed that foreign workers are on average slightly younger than their German counterparts. At the same time, tendencies towards an aging population become apparent. One of the most crucial factors when it comes to the immigrant-native wage gap is the level of educational attainment and its differences. It is striking that in the group of the least educated workers the share for Non-German workers is almost 30 percentage points higher than in the group of German workers in 2000/01. This observed difference persists over the whole period of observation. For the medium level of education an opposite relationship is encountered starting with

[12]Table A.2 in Appendix A reveals not only significant differences in immigrant-native wage gaps between metropolitan and non-metropolitan areas but also support evidence on substantial urban-rural wage differentials in Germany as recently analyzed by Brixy et al. (2022).

80% for German workers and 61% for foreign workers in 2000/01 and resulting in 77% and 65% respectively in 2018/19. It can be seen that the shares of the two groups approximate during the period of observation. Looking at the highest educational level a similar development is presented. Both groups grow over time and result in approximated values in 2018/19. In total, the trend towards a higher educated workforce is pointed out as well. The next characteristics present information on work experience. For both factors, days in employment and job tenure, values for German workers are higher in 2018/19 than in the beginning of the observed time period. In contrast to this, foreign workers provide at first an increase in both characteristics, however ending up with significantly lower values than in 2000/01.

Firm-specific characteristics are among others represented by the collective bargaining regime, which is subdivided by three groups (no collective agreement, firm level and sector level agreement). Throughout the whole period of observation, no considerable differences between German and Non-German workers within a bargaining regime are identifiable. However, the clear trend towards no collective bargaining regime coverage is obvious with a share of around 20% in 2000/01 and more than 40% in 2018/19. Regarding the firm size, that is measured by the headcount, it is revealed that foreign workers tend to be employed at larger firms until 2008/09. However, in the end of period there is a general reversal in trend. Further variables that are considered in this group are the conducted occupation and the economic sector. For reasons of clarity, the detailed presentation of all respective groups for German and Non-German workers is omitted.

Regional-specific characteristics are the regional presence of foreign population and ROR-specific fixed effects. The former reveals that Non-German workers are one average surrounded by a slightly higher share of foreign population during the whole period of observation. The general increase in the foreign population in Germany is documented as well. In addition, a higher relative presence of foreign workers in metropolitan than in non-metropolitan areas compared to German workers is documented.

5 Empirical Approach

RIF-regressions approach. In order to estimate the effect of an explanatory variable, conditional on all other factors, on other distributional statistics than the sample mean the RIF-regressions approach is applied (Firpo et al., 2018). This estimation strategy replaces the log wage, w, as the dependent variable by the recentered influence function of the statistic of interest. The influence function, $IF(w; v)$, shows the

Table 1: Descriptive statistics by nationality; 2000/01, 2008/09, 2018/19

	2000/01		2008/09		2018/19	
	German	Non-German	German	Non-German	German	Non-German
Wage:						
	128.85	103.21	128.46	103.75	132.46	102.15
	(60.54)	(43.28)	(69.81)	(53.07)	(64.07)	(50.39)
Individual characteristics						
Age:						
	39.69	38.22	41.55	39.49	41.34	40.14
	(7.95)	(8.68)	(8.19)	(7.90)	(9.13)	(8.56)
Education:						
low	5.35	33.80	4.45	27.88	3.76	20.86
	(22.51)	(47.30)	(20.62)	(44.84)	(19.02)	(40.63)
middle	80.12	60.12	78.29	61.68	76.53	64.94
	(39.91)	(48.96)	(41.23)	(48.62)	(42.38)	(47.72)
high	14.52	6.82	17.26	10.44	19.70	14.19
	(35.23)	(23.89)	(37.79)	(30.58)	(39.78)	(34.90)
Days in employment:						
	5357.09	4359.11	6311.28	4885.39	6339.73	3922.65
	(2771.81)	(2925.24)	(3112.07)	(3047.31)	(3267.43)	(3290.89)
Job tenure (days):						
	2753.02	2344.02	3258.02	2743.82	3013.37	1875.20
	(2575.06)	(2459.91)	(2853.06)	(2642.96)	(2917.51)	(2510.97)
Firm-specific characteristics						
Collective bargaining regime:						
No collective agreement	24.22	23.59	32.27	33.38	40.19	44.22
	(42.84)	(42.45)	(46.75)	(47.16)	(49.03)	(49.67)
Firm level agreement	7.84	5.89	9.87	8.97	9.93	9.41
	(26.89)	(23.55)	(29.82)	(28.56)	(29.90)	(29.20)
Sector level agreement	67.93	70.51	57.86	57.66	49.88	46.37
	(46.67)	(45.69)	(49.37)	(49.41)	(49.99)	(49.87)
Plant size:						
	1043.76	1390.41	1256.25	1307.73	1262.47	851.80
	(3829.74)	(4241.44)	(4837.03)	(4577.42)	(6485.61)	(4659.84)
Regional-specific characteristics						
Share of foreign population:						
	10.17	11.93	9.15	10.77	13.85	15.13
	(4.72)	(4.61)	(3.77)	(3.71)	(4.23)	(4.19)
Metropolitan area:						
	65.19	71.99	64.85	73.79	63.48	68.96
	(47.64)	(44.91)	(47.74)	(43.98)	(48.14)	(46.26)
Number of observations	1,521,444	152,629	1,220,476	97,041	666,154	72,840

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents descriptive statistics for selected variables in 2000/01, 2008/09 and 2018/19. The shares are multiplied by 100 for convenience. Sampling weights are employed.

influence of each observation on this distributional statistic and is dependent on the wage distribution F_w. The following linear function of explanatory variables defines how the conditional expectation of the $RIF(w;v)$ can be estimated:

$$E[RIF(w;v)|X] = X\gamma, \tag{1}$$

where the parameters γ can be estimated by OLS (Fortin et al., 2011).

Since subsequent analyses aim in estimating the effects of immigrant population on different parts of the wage distribution, the case of quantiles is used. As a consequence, the estimated coefficients are interpreted as unconditional (quantile) partial effects (UQPE) of small location shifts in the covariates (Firpo et al., 2009). In contrast to the commonly known conditional quantile regressions, it is possible to identify the effect of a changing explanatory variable on the τth quantile of the unconditional distribution of w.

Decomposition method. In order to identify the explanatory factors that drive differentials between Germans, N, and non-Germans, F, at different parts of the wage distribution, the standard decomposition method introduced by Oaxaca (1973) and Blinder (1973) (OB decomposition) on the basis of RIF regressions is applied. Assuming linear wage equations of the two groups, g, where w denotes the log wage and X is a vector of covariates, the following equation presents the standard (aggregate) decomposition of the log wage gap at the mean[13], μ:

$$\begin{aligned}\hat{\Delta}_O^{\mu} &= \bar{w}_N - \bar{w}_F \\ &= \bar{X}_N(\hat{\beta}_N - \hat{\beta}_F) + (\bar{X}_N - \bar{X}_F)\hat{\beta}_F. \end{aligned} \tag{2}$$

The first half of equation (2) represents the part that cannot be explained due to differences in explanatory factors. This term defines the unexplained, residual part of the wage gap between German and Non-German workers. The second half denotes the explained part that is based on mean differences in covariates and is called composition effect (Fortin et al., 2011).

Together with the estimated coefficients of unconditional quantile regressions, $\hat{\gamma}_{g,\tau}$[14], for each group, where $g = N, F$, the OB decomposition of equation (2) at quantile τ is

[13]The standard OB decomposition at the mean is estimated using the linear wage setting regression model $w_g = X\beta_g + v_g$, where $g = N, F$.

[14]The coefficients of the unconditional quantile regressions for each group are defined as: $\hat{\gamma}_{g,\tau} = (\sum X_i X_i')^{-1} \sum \widehat{RIF}(w_{gi}; Q_{g,\tau}) X_i$, where $g = N, F$.

defined as:

$$\hat{\Delta}_O^\tau = \bar{X}_N(\hat{\gamma}_{N,\tau} - \hat{\gamma}_{F,\tau}) + (\bar{X}_N - \bar{X}_F)\hat{\gamma}_{F,\tau} \tag{3}$$

where $\hat{\Delta}_O^\tau$ presents the wage gap at the τth unconditional quantile. Using this extended method, it is possible to decompose log wage gaps between German and Non-German workers at the level of quantiles. Further, as proposed by Firpo et al. (2018) the two-step procedure is applied decomposing wage gaps in order to fulfill the linearity assumption of the model.[15] For this reason, the reweighting function introduced by DiNardo et al. (1996) is used to construct at first a counterfactual sample, $g = C$, of Non-German workers with the distributional weights of German workers.[16]

As a result of this procedure, Fortin et al. (2011) show that the explained part of the decomposition is divided into the pure explained part as well as the specification error and is estimated by:

$$\hat{\Delta}_{X,R}^\tau = (\bar{X}_C - \bar{X}_F)\hat{\gamma}_{F,\tau} + \bar{X}_C(\hat{\gamma}_{C,\tau} - \hat{\gamma}_{F,\tau}).$$

The latter part denotes the difference between the total wage structure effect in the initial OB decomposition and the reweighted regression decomposition. Thus, the specification error should be equal to zero if the model was truly linear.

By analogy, the unexplained part can be divided into the pure unexplained part and the reweighting error, which is estimated by:

$$\hat{\Delta}_{S,R}^\tau = \bar{X}_N(\hat{\gamma}_{N,\tau} - \hat{\gamma}_{C,\tau}) + (\bar{X}_N - \bar{X}_C)\hat{\gamma}_{C,\tau}.$$

The latter part is defined as the difference between the total explained effect across the initial OB decomposition and the reweighted regression decomposition. In other words, since the counterfactual sample is used to imitate the sample of German workers, in large samples it should be $plim(\bar{X}_C) = plim(\bar{X}_N)$. This results in a reweighting error that goes to zero, if the reweighting factor $\hat{\psi}(X)$ is consistently estimated.

[15] As discussed by Barsky et al. (2002), if the linearity assumption in the case of the standard OB decomposition does not hold, the estimated counterfactual mean wage would not be equal to $\bar{X}_N\hat{\beta}_F$.

[16] The reweighting function is estimated as follows:

$$\hat{\psi}_X(X) = \frac{Pr(g = F)}{Pr(g = N)} \frac{Pr(g = N|X)}{Pr(g = F|X)},$$

where $Pr(g = N)$ and $Pr(g = F)$ denote the sample proportions of German and Non-German workers in the pooled data. The proportions $Pr(g = N|X)$ and $Pr(g = F|X)$ are reminiscent of a standard binary dependent variable. Therefore, the likelihood that an individual belongs to one of either groups conditional on the covariates X can be estimated using a logit or a probit model based on the pooled sample (Fortin et al., 2011).

The underlying decomposition method ascribes estimated wage differentials between two groups completely to the considered covariates. Thus, the sum of all detailed explained and unexplained effects defines the overall wage gap between German and Non-German workers at a specific quantile. This feature has to be taken into account when it comes to the interpretation of the unexplained effect of the decomposition. In the literature, this effect is commonly equated with a measure of discrimination against foreign workers (Fortin et al., 2011). Nevertheless, it also contains possible effects resulting from group differences of predictors that are unobserved in the analysis (Jann 2008; Lehmer and Ludsteck 2011). It is obvious that it is not possible to observe all potential causes that lead to differences in wages. Soft skills such as communication, motivation but also assertiveness in negotiations as well as cultural differences can hardly be represented as they are in reality (Ingwersen and Thomsen, 2021). The unexplained part of wage gaps is also sometimes claimed as productivity differences between German and foreign workers since by definition comparable characteristics are remunerated differently and thus differences in the slopes of the estimated wage equations can be observed (Brunow and Jost, 2019). As a result of these considerations, the respective part of wage gaps is named unexplained effect in the following and serves only as an indication on how well integrated foreign workers are in the German labor market.

Model specification. Individual explanatory factors are represented by the age and its square as well as the educational level of workers (three dummy variables[17]). Regarding the individual work experience, the days in employment and the days of job tenure as well as their squared values are considered. Further, 14 different occupational segments based on the 2-digit Classification of Occupations 2010 (Klassifizierung der Berufe 2010, KldB 2010) are taken into account to control for occupation related effects. Firm-specific properties such as the economic sector (19 groups based on the Classification of Economic Activities, WZ 2008), the firm size (six dummy variables[18]) and the bargaining regime (three groups[19]) augment the explanatory factors. Regional-specific effects are controlled by the share of foreign population and dummy variables indicating ROR-regions.

[17](1) Low: lower/middle secondary without vocational training; (2) Medium: lower/middle secondary with vocational training or upper secondary with or without vocational training; (3) High: university of applied sciences or traditional university.

[18](1) 1-9 employees; (2) 10-49 employees; (3) 50-199 employees; (4) 200-999 employees; (5) 1000-4999 employees; (6) $\geq$5000 employees.

[19](1) Sector-level agreement; (2) Firm-level agreement; (3) No collective bargaining agreement.

6 Decomposition Results

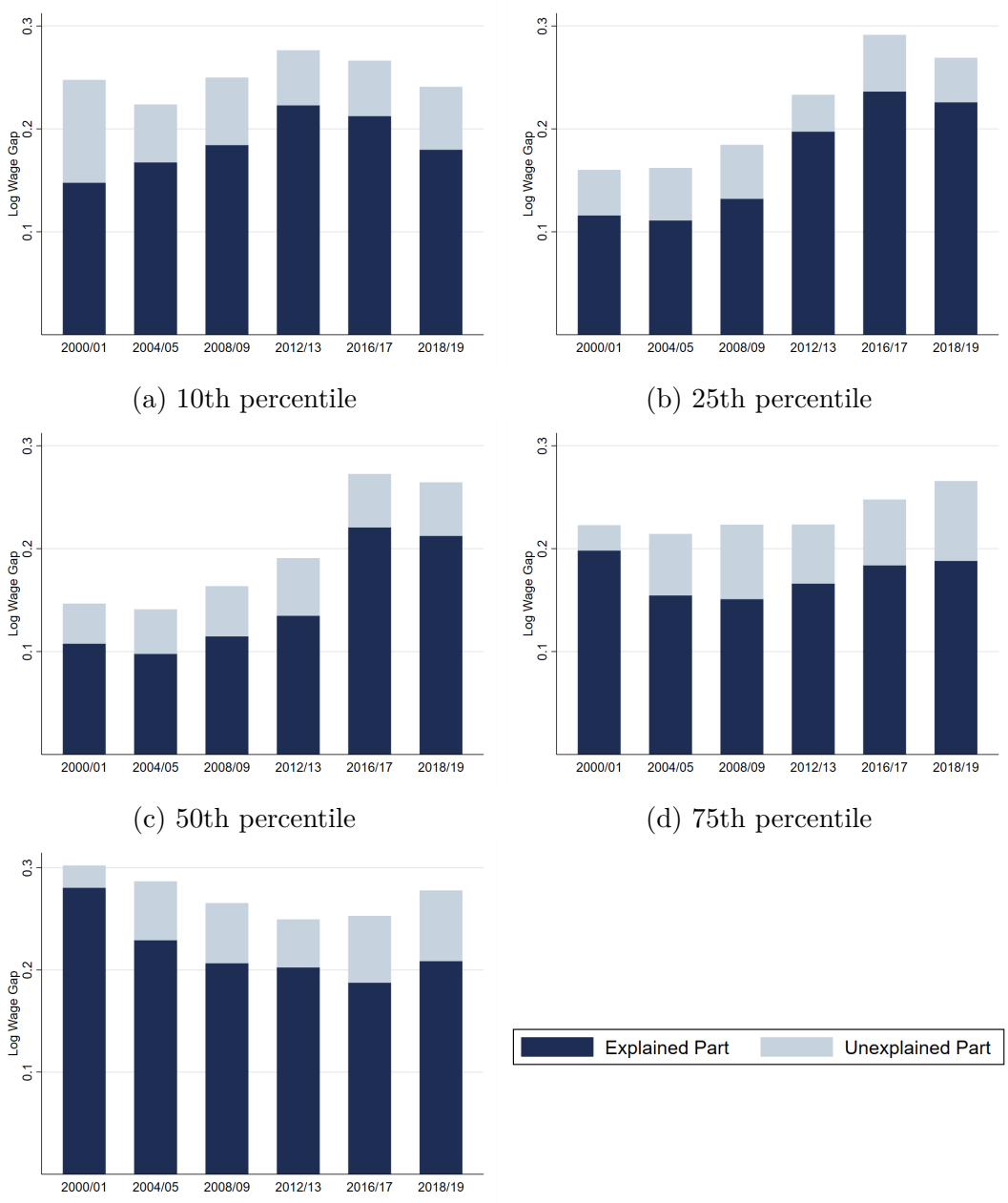
6.1 Aggregate Decomposition

Using RIF-regressions based Oaxaca-Blinder decompositions, it is possible to divide estimated log wage gaps at different percentiles into an endowment effect that is explained by differences in characteristics and into a coefficient effect that represents the unexplained part due to different returns to observed characteristics. The aim of the aggregate decomposition is to show, to which extent wage differentials are caused by differences in observed characteristics and which part is left to unexplained effects. High values of the latter would provide indications on possible differences regarding the remuneration of foreign workers compared to Germans. In this context, discriminatory employment patterns such as sticky floors and glass ceiling, where it is nearly impossible to either leave lower wage structures or reach higher valued jobs for Non-German workers, could be identified.

Overall wage gaps. Figure 6 presents the results of the aggregate decompositions for the 10th, 25th, 50th, 75th and 90th percentiles at pooled time points (2000/01, 2004/05, 2008/09, 2012/13, 2016/17 and 2018/19)[20]. In general, the majority of respective wage gaps results due to differences in explanatory factors and unexplained parts account only for smaller extents. Further, whereas the former is at any time and percentile statistically significant at the 1% level, the latter is insignificant throughout the whole period.

Subfigure (a) presents log wage gaps for the lowest wages (10th percentile), where the difference between German and Non-German workers stays between 2000/01 (0.25) and 2018/19 (0.24) more or less stable with an ambiguous trend in between. The endowment effect explains around 80% in 2008/09, 2016/17 and 2019/18, whereas the coefficient effect has a maximum of 40% in 2000/01. A different development of log wage gaps is encountered at the 25th percentile and median wages. In 2000/01, differences amount for 0.15 log points and increase up to 0.26 log points in 2018/19, respectively. Differences in observable characteristics explain between 69% (2004/05) and 85% (2018/19) of the overall log wage gaps at the 25th percentile. At median wages, the extent of unexplained effects decreases as well over time by around 10 percentage points. A stable pattern is presented in subfigure (d), where wage differentials are around 22% at the 75th percentile between 2000/01 and 2016/17. However, in the last

[20]Due to the availability of data only until 2019, there is no distance between the two last time points. However, due to the special relevance of this time period, regarding migration developments, both time points are considered.



(a) 10th percentile

(b) 25th percentile

(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure 6: Aggregate decomposition of immigrant-native wage gaps along the wage distribution, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The different subfigures present the estimated results of the RIF-regressions based aggregate OB decomposition. Sampling weights are employed.

year of observation an outlier up to 27% is observable. In addition, a trend towards a larger unexplained effect of wage differentials is presented. Whereas in 2000/01 the wage gap was not explainable by differences in characteristics by around 11%, the effect increases to almost 30% in 2018/19. At the highest wages (90th percentile) the development is once again different, where the overall log wag gaps decrease over time

until 2016/17 with an increase thereafter in 2018/19. As already seen before, a trend towards a larger unexplained part is presented. In 2000/01 the wage gap between German and Non-German workers is almost completely explainable by differences in the observable characteristics. However, the unexplained part begins to increase since 2004/5 with 20% and amounts in 2018/19 around 25%.

As presented above, the group of foreign workers in Germany consists out of various nationalities with different motives of settlement and time points of immigration. In order to account for possible heterogeneity among Non-German workers, the aggregate analysis is estimated separately on the one side between German workers and workers of EU countries[21] as well as on the other side between German workers and workers from the rest of the world. Table A.3 and Table A.4 in Appendix A reveal not only significant differences in magnitudes of estimated wage differentials but also variation in the decomposition in explained and unexplained effects. At any point along the wage distribution, wage gaps are higher for Non-EU than for EU workers with a reversal in trend after 2012/13. Further, wage differentials of EU citizens are entirely explainable by differences in observable characteristics of workers. In contrast to this, Non-EU citizens experience wage gaps that are explained at the most by only 50% due to composition effects. These observations are partly results of distinctions in the legal access of foreign workers to the German labor market. In general, there is a substantially easier access for workers of EU countries compared to workers from the rest of the world that are confronted by specific regulations and required permissions (see Brunow and Jost, 2019). Thus, regarding the extent of unexplained effects and resulting measures by policy makers, the observed group of foreign workers and their characteristics play a decisive role.

Regional differences. The decomposition analyses based on regional differences are estimated separately for metropolitan and non-metropolitan areas. Figure B4 in Appendix B presents respective aggregate decompositions. Having a closer look at overall wage gaps in metropolitan areas, the same developments at different wage percentiles over time can be seen as presented above. In contrast to this, significantly lower values of wage differentials are identified in non-metropolitan areas between 2000/01 and 2012/13 at the selected percentiles. Further, the results indicate higher shares of unexplained effects in urban areas, especially for the lower half of the distribution, during this period. Until 2012/13, the unexplained part is on average 13 percentage points higher in metropolitan than in non-metropolitan areas. Thereafter, overall wage

[21] The group of EU-citizens is defined according to the member states of the European Union at the time of observation.

gaps and divisions of effects within the aggregate decomposition seem to adjust. In 2018/19, overall wage gaps in non-metropolitan areas are even higher than those in urban regions, except for top wages at the 90th percentile.

6.2 Detailed Decomposition

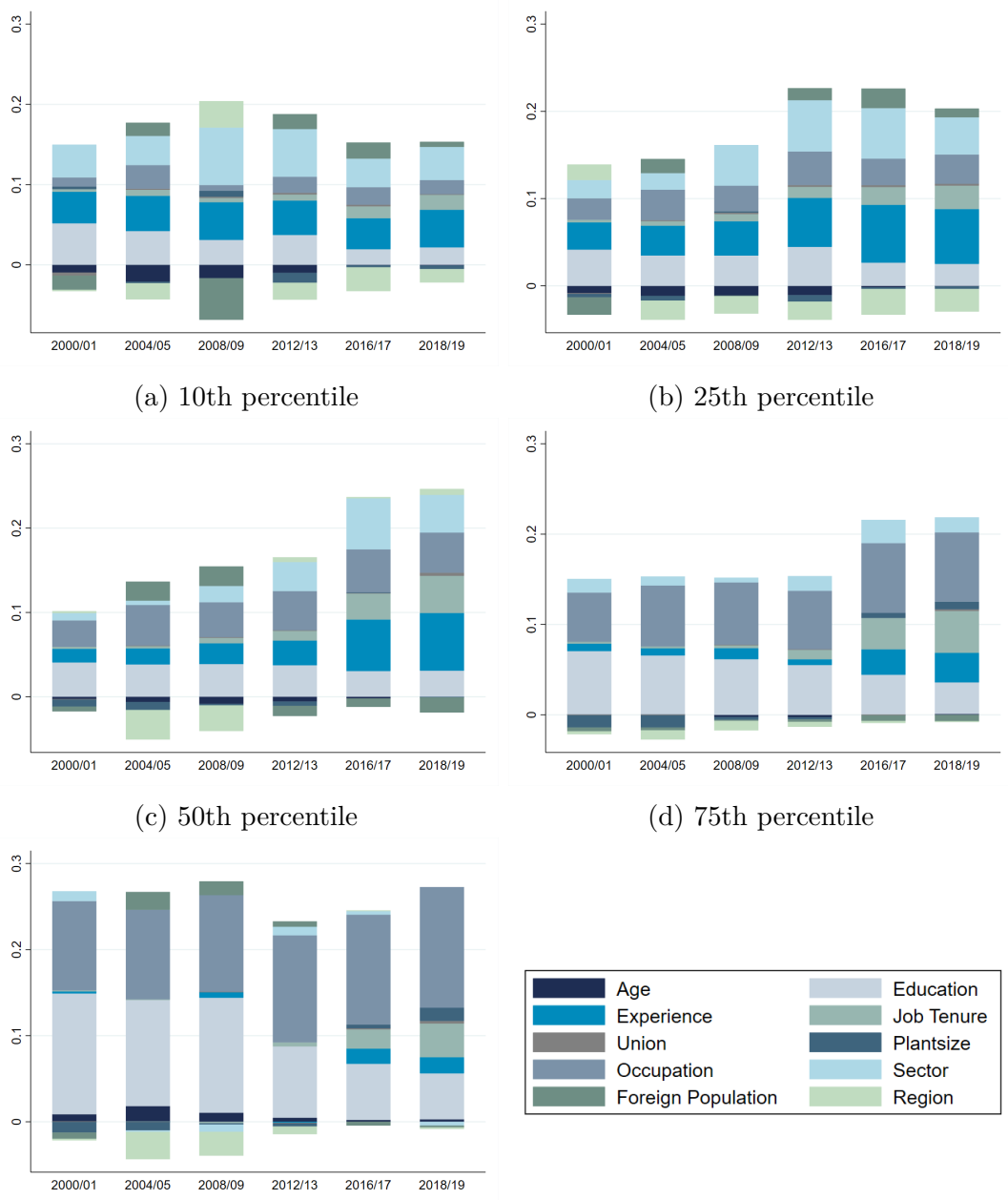
In order to identify to which extent various explanatory factors influence wage differentials between German and foreign workers, unconditional quantile regressions are estimated in a first step. Since it is the main interest to show results of detailed decompositions, estimations of RIF-regressions are not presented in detail. As seen in the section before, differences in observed characteristics explain mainly the estimated immigrant-native wage gaps and are statistically significant. Due to the fact that unexplained parts play only a minor role and no statistically significant driving factors are detected, the focus of this section is on the detailed decomposition of endowment effects.

Overall wage gaps. Figure 7 presents detailed decompositions of endowment effect at different points of the wage distribution (10th, 25th, 50th, 75th and 90th percentile) over the time span of 19 years (2000-2019).[22] In general, it is obvious that the relative roles of the explanatory factors differ between the selected percentiles and over time.

The results reveal that differences in educational levels are one of the important factors driving wage gaps between German and foreign workers. As seen in the descriptive statistics, considerable differences are especially identified during the first half of the observed time period. As a result of these varieties, educational differences explain circa one quarter of the endowment effect at the lower half of the wage distribution in 2000/01. For workers at the 75th and 90th percentiles, wage gaps are even explainable by more than 30% and 40% due to differences in educational levels until 2008/09. However, at all parts of the wage distribution a general trend towards a decreasing influence of educational attainment is observable over time. In 2018/19, only between 10% and 19% are still explained by differences in education. This development is attributable to the shrinking gap in higher levels of education between German and Non-German workers presented in the descriptive statistics.

Different developments are seen regarding the factors days in employment and job tenure, whose effects are as well all highly significant. Starting with days in employment, the results reveal an impact of around 20% for lower wage gaps during the whole

[22]The detailed decomposition is conducted applying the proposed two step procedure by DiNardo et al. (1996), where at first a counterfactual distribution is estimated. Thus, in Figure 7 only the pure composition effects are illustrated. The predominantly statistically insignificant specification errors are omitted. Further, all underlying detailed results to the Figures are presented in Tables A.5-A.10 in Appendix A.



(a) 10th percentile

(b) 25th percentile

(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure 7: Detailed decomposition of the explained part, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The different subfigures present the estimated results of the RIF-regressions based detailed OB decomposition. Sampling weights are employed.

period. In contrast to this, for median wage gaps and at the 75th percentile the effects increase from 10% and 5% to more than one quarter and 15%, respectively. For wage gaps at the 90th percentile, differences in days of employment only play a noticeable role in the last two time points. Turning to differences in job tenures, a similar trend is identified. According to the estimated results, the respective impacts increase from almost zero to more than 10% (10th, 25th and 90th percentile) and 15% (50th and 75th percentile) between 2000/01 and 2018/19. Thus, the results provide evidence of a growing impact on wage gaps along the whole distribution due to differences in days of employment and job tenure.

Distinct effects on wage gaps at the lower half of the wage distribution result from differences in the sectoral employment of workers. Between 15% and one quarter are explainable due to different selections of sectors. For median wages, impacts of sectoral differences increase in importance from 7% in 2000/01 up to 24% in 2016/17. At the upper part of the wage distribution, there is almost no significant effect coming from different sectoral employment. The complete opposite development is observable for effects due to occupational differences between 2000/01 and 2018/19. On the one side, the effects range between 3% and 15% in the lower half of the wage and explain circa 20% of median wage gaps. On the other side, differences in occupational fields are the main driving force of endowment effects at the 75th and 90th percentiles. The impact increases between 2000/01 and 2018/19 from around one third to more than 50% for highest wages. The results show that while at the bottom of the wage distribution differences between German and Non-German workers arise due to sectoral impact, it is revealed that at higher wages occupational differences play the most important role.

Another, until now less observed, factor behind wage gaps between German and Non-German workers are possible effects due to differences in the regional presence of the foreign population. In general, no consistent positive or negative effects on wage differentials along the distribution are identified. However, mainly statistically significant and positive impacts are observed for wage gaps at the 10th and 25th percentiles ranging between 3% and 10% from 2000/01 to 2018/19. Further, wage gaps at the median and the 90th percentile exhibit increasing tendencies due to differences in the presence of the foreign population mainly between 2004/05 and 2012/13. The estimated negative effects that are mainly observed at the 75th percentile, are either statistically not significant or show effects of only a marginal share.

Explanatory variables that only play a minor role in describing endowment effects between German and Non-German workers are differences in age, region of employment and collective bargaining regime of the firm. Most of the time these effect are negative and mainly statistically insignificant. The factor that has a reducing impact

on endowment effects is the size of the plant of employment, whose coefficients are mainly statistically significant.

Regional Differences. This study further presents detailed decomposition analyses of wage differentials separately for metropolitan and non-metropolitan areas in Germany. As seen before, there are significant regional differences in levels of wage gaps between German and Non-German workers suggesting a varied composition of the respective workforce. Figures B5 and B6 in Appendix B present estimation results of the explained parts at common wage percentiles.

In general, the above identified trends regarding decreasing impacts of educational attainment and growing effects due to differences in professional experience are revealed as well. However, the respective magnitudes differ significantly regarding the former. Whereas differences in levels of education explain composition effects at the lower half of the distribution by around 10% (2000/01-2018/19) in non-metropolitan areas, this effect almost doubles in size for metropolitan regions. The same results for median and top wages, where the impact is at least 10 percentage points higher in urban areas. These results provide evidence for regional-specific higher discrepancies between German and foreign workers in metropolitan areas in seeking for higher levels of education. Table A.2 in Appendix A provides additional area-specific descriptive statistics, where a general pattern is revealed. In metropolitan areas, the shares of highest educational groups are for both, German and Non-German workers, at any point higher than in non-metropolitan areas. However, the percentage point difference within the former region between German and foreign workers is more pronounced. From this, the assumption results that Non-German workers do not benefit to the same extent as their German counterparts of better access to further education and professional development in metropolitan areas leading to higher wage gaps. Further, the estimations reveal a stronger impact (on average 5 percentage points higher) due to sectoral differences of employment at the 25th, 50th and 75th percentiles in non-metropolitan areas. Effects due to occupational differences account for similar values of the explained parts in both sub-regions. The observed effects due to regional differences in the presence of the foreign population seem to be more distinct in urban areas between 2004/05 and 2012/13 for lower wages and the median. In non-metropolitan areas, the results reveal impact especially on higher wages during the entire period of observation.

To sum up, wage differentials between German and Non-German workers do not only differ in size depending on the observed region, but also the specific compositions of explained effects vary. Since these findings provide evidence on possible regional-

specific dependencies, these results are of special interest for policy related implications.

Robustness checks. The regional specific decomposition analyses are based on the definition of metropolitan regions of West Germany by the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022) in 2008 (Wacker, 2016), which is approximately the middle of the observed time period and therefore should provide suitable information in total. However, due to economic progress during the last years, one could argue that the estimation results could be biased. In the end of the period, the defined non-metropolitan areas could contain ROR-regions that already exhibit characteristics and wage structures of metropolitan areas resulting in, on average, higher wage differentials. As a consequence of that, the decomposition analyses for pooled time points 2016/17 and 2018/19 are estimated using the division of metropolitan areas published by the Initiative Circle European Metropolitan Regions in Germany (IKM) (2022) in 2015. The estimated results show no differences regarding the size and decomposition of the wage gaps.

Further, the decomposition analyses consider regional differences in the presence of the foreign population in the same year. Possible impact on wage differences probably evolve over time. Because of this and also in order to circumvent possible biased estimated due to reversed causality, the decomposition analyses are estimated using lagged data on shares of regional foreign population by two years. The estimated results reveal no differences regarding the effect on explained and unexplained parts of detailed wage gap decompositions.

7 Discussion and Conclusion

During the last years Germany experienced noticeable increases in the share of the foreign population. One factor in order to assess effective integration of foreign workforce in the German labor market is provided by analyses on how Non-German wages evolve over time in comparison to their German counterpart. This study finds evidence of a reversal in trend for wage differentials at different parts of the wage distribution after 2012. While log wage gaps of bottom and top wages increase again and persist at a high level, wage differentials in the middle of the distribution increase for the first time significantly in the observed period between 2000 and 2019. Further, on average significantly higher wage differentials are revealed for metropolitan areas, where as well on average a higher share of foreign population is encountered.

Using the RIF-regressions based Oaxaca-Blinder decomposition method detailed analyses along the entire wage distribution are estimated. Aggregate decompositions

indetify substantial differences in the size of log wage gaps at different parts of the wage distribution, where in all cases the majority can be explained by differences in observed characteristics. However, while there is a decreasing trend in relative size of the unexplained part in the lower half of the wage distribution, the impact of differences in the returns to the observed characteristics increase at the 75th and especially for wages at the 90th percentile over time. This observation confirms findings of Lehmer and Ludsteck (2011), who show larger unexplained effects at the bottom of the wage distribution, which is seen as evidence for sticky floors, between 1995 and 2000. The presented aggregate decompositions of wage gaps in metropolitan areas reveal especially for lower wages evidence on sticky floors. In contrast to this, larger coefficients effects at the top of the distribution during recent years indicate evidence on limitations in career progression of foreign workers in Germany. This phenomenon, which is in the literature described as glass ceiling, suggests that mainly well-educated foreign workers lag behind native workers with the same characteristics and they are not included in the German labor market corresponding to their qualifications.

Applying the detailed decomposition analysis, this study provides insights in the driving factors behind wage differentials between German and Non-German workers until 2019. There is not only evidence for changes in the relative importance of explanatory factors over time but also the sources of possible wage disadvantages of foreign workers shift between different parts of the wage distribution. Evidence for a shrinking relative effect due to differences in educational attainment independent of the position at the wage distribution are contrary to the often mentioned and easier explainable differences in pay solely due to a presumed lower educated foreign workforce. Further, the wage gap in the lower half of the distribution is explained to large parts by differences in the sector of employment. Despite the fact that the analysis covers only full-time working employees, it seems that there is a certain allocation to lower paid economic sectors for Non-German workers. These findings are in line with the identified relationship by Glitz (2014) that less workplace segregation of foreign workers in Germany is closely related to improvements in their wage positions. In contrast to this, at the upper half of the distribution wage differentials mainly occur due to variation in the exercised occupation. Especially for top wage employees, this development becomes apparent and is once more evidence for possible restrictions in promotion opportunities of foreign workers. This inference is supported by Beyer (2019), who identifies less success of immigrants in obtaining jobs with higher occupational autonomy. Another crucial factor explaining wage gaps, are identified differences in labor market experience. Especially during recent years this aspect gained increasing impact on wage differentials suggesting deficits in acquiring job related knowledge

to the detriment of foreign remuneration. This striking development is supported by findings of Brunow and Jost (2020), who trace the observed significantly lower work experience among foreign workers back to the gradual opening of the German labor market during the last 15 years. In addition to the commonly observed control factors, this study provides new insights on impact due to differences in the presence of foreign population on wage gaps. Increasing tendencies in wage differentials are especially identified for lower wages, providing evidence on widening wage distributions between native and foreign workers in this area.

Another contribution of this study are region-dependent detailed decomposition analyses of wage gaps in metropolitan and non-metropolitan areas. There are not only differences in the magnitude of immigrant-native wage gaps, but there is also variation in the composition of the driving forces. Especially higher effects due to differences in educational attainment in metropolitan areas identify structural disparities between German and foreign workers regarding inequitable access to continuing education. These findings also support the presented reasoning of Warman (2007) and Schaffner and Treude (2014) in the context of residential clustering. Further, despite the fact that a close connection to co-ethnic population enhances employment of Non-German workers (Kanas et al., 2012), the presented estimations reveal deficits in the inclusion of foreign workers in labor markets of metropolitan regions. Future research could therefore attempt to identify further differences between metropolitan and non-metropolitan labor markets regarding immigrant-native wage differentials.

The identified results confirm the importance of detailed decomposition analyses of immigrant-native wage differentials along the entire wage distribution for specific time points across different regions in Germany between 2000 and 2019. In doing so, the study contributes important insights in an indirect measure of how foreign workers are assimilated into the German labor market and can integrate into society.

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A Appendix A

Table A.1: Overview of changes in the composition of districts between 2000 and 2019

Initial district	Merging and current district	Year of change
Hannover, independent town	Hannover, district	2001
Aachen, independent town	Aachen, city region	2009
Osterode am Harz	Göttingen	2016

Source: (Federal Bureau of Statistics (Destatis), 2021a).
Notes: The table presents the mergers of districts between 2000 and 2019. The affected districts are considered as one during the whole period of observation.

Table A.2: Additional descriptive statistics by nationality; 2000/01, 2008/09, 2018/19

	2000/01		2008/09		2018/19	
	German	Non-German	German	Non-German	German	Non-German
Wage:						
Metropolitan area	133.62	104.46	134.16	106.21	136.17	105.05
	(64.16)	(44.83)	(75.55)	(55.75)	(67.83)	(52.73)
Non-metropolitan area	119.91	100.00	117.95	96.81	126.01	95.69
	(51.94)	(38.82)	(56.24)	(44.52)	(56.38)	(44.10)
Individual characteristics						
Education:						
low						
Metropolitan area	5.16	34.38	4.40	27.73	3.82	20.10
	(22.13)	(47.50)	(20.50)	(44.76)	(19.16)	(40.08)
Non-metropolitan area	5.71	32.32	4.55	28.33	3.82	20.10
	(23.20)	(46.77)	(20.85)	(45.06)	(19.6)	(40.08)
middle						
Metropolitan area	78.51	58.90	76.09	61.04	74.35	64.47
	(51.07)	(49.20)	(42.65)	(48.77)	(43.67)	(43.67)
Non-metropolitan area	83.14	63.26	82.36	63.48	80.32	65.95
	(37.44)	(48.21)	(38.12)	(48.15)	(39.75)	(47.39)
high						
Metropolitan area	16.33	6.73	19.52	11.24	21.83	15.41
	(39.96)	(25.05)	(39.63)	(31.58)	(41.31)	(36.10)
Non-metropolitan area	11.15	4.42	13.09	8.19	16.02	11.50
	(31.47)	(20.56)	(33.73)	(27.42)	(36.68)	(31.91)
Regional-specific characteristics						
Share of foreign population:						
Metropolitan area	12.01	13.57	10.47	11.87	15.38	16.60
	(4.76)	(4.30)	(3.84)	(3.42)	(4.54)	(4.12)
Non-metropolitan area	6.79	7.85	6.63	7.42	11.51	12.17
	(2.02)	(2.39)	(1.84)	(2.22)	(2.25)	(2.42)

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents descriptive statistics for selected variables in 2000/01, 2008/09 and 2018/19. The shares are multiplied by 100 for convenience. Sampling weights are employed.

Table A.3: Aggregate decomposition results, German and EU workers

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
2000/01										
Log wage gap	19.42***	(2.64)	9.54***	(0.99)	10.05***	(0.56)	13.17***	(0.73)	16.97***	(1.18)
Composition effect	20.48***	(2.88)	8.79***	(1.98)	10.09***	(1.75)	13.55***	(3.15)	18.36***	(3.05)
Wage structure effect	−1.06	(15.98)	0.74	(12.32)	−0.04	(8.77)	−0.38	(22.70)	−1.39	(20.61)
2004/05										
Log wage gap	13.60***	(2.69)	7.34***	(1.03)	7.42***	(0.67)	11.62***	(0.65)	14.08***	(1.14)
Composition effect	15.16***	(2.79)	7.32***	(1.58)	6.95***	(1.34)	7.57***	(1.43)	13.67***	(2.14)
Wage structure effect	−1.56	(13.33)	0.02	(10.10)	0.47	(8.57)	4.05	(9.83)	0.41	(14.97)
2008/09										
Log wage gap	21.57***	(2.20)	12.89***	(1.02)	10.87***	(0.72)	13.52***	(0.72)	10.99***	(1.18)
Composition effect	22.03***	(3.15)	12.08***	(1.77)	9.84***	(1.37)	13.13***	(1.85)	13.44***	(2.39)
Wage structure effect	−0.46	(23.40)	0.81	(13.28)	1.03	(9.66)	0.39	(1.71)	−2.45	(19.59)
2012/13										
Log wage gap	28.21***	(1.38)	23.77***	(1.22)	17.84***	(0.84)	14.68***	(1.22)	10.02***	(1.55)
Composition effect	27.60***	(2.95)	24.58***	(1.82)	18.12***	(1.58)	17.90***	(2.30)	13.01***	(2.93)
Wage structure effect	0.61	(19.86)	−0.81	(12.60)	−0.28	(11.02)	−3.22	(15.89)	−2.99	(21.98)
2016/17										
Log wage gap	27.51***	(0.89)	32.70***	(0.75)	32.68***	(0.81)	27.97***	(1.01)	21.43***	(1.21)
Composition effect	26.05***	(3.41)	32.80***	(2.22)	33.58***	(2.02)	31.63***	(2.19)	23.75***	(2.07)
Wage structure effect	1.46	(21.07)	−0.10	(12.98)	−0.89	(11.65)	−3.67	(13.02)	−2.32	(12.26)
2018/19										
Log wage gap	25.16***	(1.02)	29.16***	(0.84)	30.50***	(0.74)	30.64***	(0.93)	25.31***	(1.29)
Composition effect	23.04***	(5.96)	28.77***	(2.05)	31.04***	(2.00)	33.04***	(2.57)	28.58***	(2.37)
Wage structure effect	2.12	(31.59)	0.39	(10.86)	−0.54	(10.95)	−2.40	(14.70)	−3.27	(13.49)

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the aggregate RIF-regressions based OB decomposition approach between German and EU foreign workers based on log daily wages for all considered percentiles. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.4: Aggregate decomposition results, German and Non-EU workers

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
2000/01										
Log wage gap	26.54***	(1.84)	19.39***	(0.74)	17.89***	(0.42)	26.33***	(0.39)	38.01***	(0.52)
Composition effect	10.35***	(3.53)	10.16***	(1.62)	9.25***	(1.11)	15.73***	(1.89)	30.56***	(6.33)
Wage structure effect	16.19	(13.47)	9.23	(6.14)	8.63	(4.00)	10.60	(6.28)	7.44	(22.79)
2004/05										
Log wage gap	26.84***	(1.34)	20.75***	(0.75)	18.25***	(0.52)	27.09***	(0.40)	37.25***	(0.64)
Composition effect	20.61***	(2.42)	14.70***	(1.02)	10.41***	(1.74)	15.17***	(2.37)	24.46***	()
Wage structure effect	6.23	(10.61)	6.01	(3.57)	7.83	(4.81)	15.17	(2.24)	12.80	(15.14)
2008/09										
Log wage gap	26.27***	(1.28)	21.89***	(0.79)	19.45***	(0.59)	27.12***	(0.53)	36.32***	(0.80)
Composition effect	14.24***	(2.66)	12.86***	(1.66)	11.02***	(1.21)	14.68***	(1.62)	18.77***	(2.46)
Wage structure effect	12.03	(13.00)	9.03	(7.32)	8.43	(5.66)	12.44	(7.71)	17.55	(12.72)
2012/13										
Log wage gap	26.66***	(1.11)	22.97***	(0.82)	19.90***	(0.57)	25.94***	(0.58)	34.71***	(0.64)
Composition effect	15.09***	(3.07)	15.66***	(1.80)	10.72***	(1.44)	14.04***	(1.80)	16.53***	(1.87)
Wage structure effect	11.57	(12.54)	7.31	(7.47)	9.18	(5.12)	11.90	(6.27)	18.17	(8.04)
2016/17										
Log wage gap	25.46***	(1.08)	22.92***	(0.86)	20.92***	(0.77)	22.59***	(0.60)	29.11***	(0.86)
Composition effect	17.30***	(2.23)	13.93***	(1.48)	10.99***	(1.44)	9.67***	(1.45)	12.59***	(3.25)
Wage structure effect	8.16	(10.17)	8.98	(6.33)	9.93	(6.19)	12.92	(6.24)	16.52	(14.61)
2018/19										
Log wage gap	23.30***	(0.93)	24.15***	(0.84)	21.00***	(0.80)	23.71***	(0.58)	30.02***	(0.79)
Composition effect	15.88***	(2.65)	17.01***	(1.35)	12.02***	(1.38)	9.45***	(1.51)	10.98***	(2.18)
Wage structure effect	7.42	(12.02)	7.14	(5.89)	9.00	(5.97)	14.26	(6.46)	19.04	(8.47)

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the aggregate RIF-regressions based OB decomposition approach between German and Non-EU foreign workers based on log daily wages for all considered percentiles. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.5: Detailed decomposition results, 2000/01

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	24.75***	(1.70)	16.01***	(0.65)	14.65***	(0.35)	22.28***	(0.37)	30.22***	(0.54)
Pure composition effect										
Age	−0.95***	(0.14)	−0.84***	(0.08)	−0.30***	(0.05)	0.05***	(0.05)	0.88***	(0.07)
Education	5.18***	(0.23)	4.16***	(0.14)	4.08***	(0.14)	7.01***	(0.28)	14.03***	(0.07)
Work experience	3.92***	(0.28)	3.11***	(0.23)	1.60***	(0.16)	0.82***	(0.13)	0.23**	(0.09)
Job tenure	0.34***	(0.10)	0.32***	(0.08)	0.25***	(0.07)	0.21**	(0.09)	0.14	(0.09)
Collective bargaining	−0.39	(0.33)	−0.08	(0.09)	−0.04**	(0.02)	−0.05***	(0.01)	−0.02	(0.03)
Plant size	0.33	(0.53)	−0.38*	(0.23)	0.81***	(0.12)	−1.35***	(0.12)	−1.23***	(0.14)
Occupation	1.13***	(0.33)	2.46***	(0.14)	3.13***	(0.18)	5.45***	(0.35)	10.36***	(0.71)
Sector	4.08***	(0.68)	2.09***	(0.24)	0.88***	(0.24)	1.51***	(0.31)	1.14**	(0.51)
Foreign share	−1.76***	(0.40)	−2.00***	(0.24)	−0.57***	(0.11)	−0.43**	(0.17)	−0.72**	(0.32)
Region	−0.18	(0.74)	1.77***	(0.42)	0.22	(0.25)	−0.31	(0.30)	−0.19	(0.47)
Total	11.70***	(1.31)	10.58***	(0.58)	8.43***	(0.35)	12.91***	(0.59)	24.61***	(1.12)
Specification error	3.07	(2.53)	1.01	(1.09)	2.33*	(1.20)	6.92***	(1.75)	3.43	(2.61)
Pure wage structure effect										
Total	7.30	(8.29)	4.00	(3.81)	5.12*	(3.07)	5.74*	(3.12)	3.95	(7.04)
Reweighting error	2.68	(3.52)	0.41	(1.69)	−1.23	(1.89)	−3.29	(2.68)	−1.77	(3.30)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2000/01. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.6: Detailed decomposition results, 2004/05

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	22.37***	(1.14)	16.20***	(26.71)	14.11***	(0.39)	21.43***	(0.41)	28.67***	(0.63)
Pure composition effect										
Age	−2.09***	(0.13)	−1.15***	(0.07)	−0.60***	(0.05)	0.06	(0.04)	1.83***	(0.10)
Education	4.21***	(0.13)	3.49***	(0.11)	3.84***	(0.13)	6.51***	(0.28)	12.32***	(0.71)
Work experience	4.38***	(0.22)	3.41***	(0.18)	1.90***	(0.13)	0.79***	(0.909)	−0.02***	(0.05)
Job tenure	0.76***	(0.15)	0.52***	(0.10)	0.33***	(0.06)	0.22***	(0.05)	0.09***	(0.02)
Collective bargaining	0.14*	(0.08)	0.12	(0.09)	0.02	(0.05)	−0.05**	(0.02)	−0.00	(0.00)
Plant size	−0.19	(0.42)	−0.54**	(0.09)	−0.96***	(0.16)	−1.34***	(0.12)	−0.98***	(0.12)
Occupation	2.94***	(0.18)	3.49***	(0.16)	4.80***	(0.18)	6.73***	(0.25)	10.41***	(0.45)
Sector	3.63***	(0.40)	1.89***	(0.15)	0.52***	(0.11)	1.01***	(0.19)	−0.17***	(0.37)
Foreign share	1.64***	(0.12)	1.62***	(0.10)	2.25***	(0.16)	−0.32***	(0.12)	2.05***	(0.25)
Region	−2.92***	(0.44)	−2.20***	(0.18)	−3.51***	(0.24)	−1.03***	(0.16)	−3.18***	(0.31)
Total	13.41***	(0.76)	10.65***	(0.41)	8.58***	(0.33)	12.58***	(0.53)	22.34***	(0.88)
Specification error	0.33	(2.27)	0.45	(1.17)	1.20	(0.98)	2.88**	(1.38)	0.58	(3.17)
Pure wage structure effect										
Total	2.96	(2.55)	3.62	(3.87)	4.19	(3.17)	7.15	(3.95)	7.66	(10.34)
Reweighting error	2.96	(8.39)	1.47	(1.56)	0.13	(1.45)	−1.17	(2.21)	−1.90	(3.95)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2004/05. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.7: Detailed decomposition results, 2008/09

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	24.98***	(1.16)	18.45***	(0.69)	15.36***	(0.46)	22.33***	(0.46)	26.54***	(0.80)
Pure composition effect										
Age	−1.65***	(0.11)	−1.16***	(0.07)	−0.83***	0.06()	−0.24***	(0.03)	1.06***	(0.08)
Education	3.11***	(0.11)	3.47***	(0.11)	3.88***	(0.11)	6.16***	(0.22)	13.35***	0.67()
Work experience	4.70***	(0.21)	3.93***	(0.17)	2.47***	(0.12)	1.23***	(0.06)	0.68***	(0.06)
Job tenure	0.52***	(0.06)	0.83***	(0.08)	0.67***	(0.07)	0.35***	(0.04)	−0.17***	(0.03)
Collective bargaining	0.16**	(0.08)	0.17**	(0.08)	0.07	(0.04)	0.03	(0.03)	0.03	(0.03)
Plant size	0.73**	(0.30)	0.14	(0.17)	−0.18	(0.15)	−0.32**	(0.13)	−0.15	(0.11)
Occupation	0.73***	(0.17)	2.94***	(0.11)	4.14***	(0.12)	6.88***	(0.20)	11.21***	(0.35)
Sector	7.16***	(0.34)	4.67***	(0.21)	1.93***	(0.12)	0.53***	(0.16)	−0.85***	(0.36)
Foreign share	−5.21***	(0.52)	−0.03	(0.22)	2.31***	(0.20)	−0.12	(0.08)	1.61***	(0.18)
Region	3.29***	(0.62)	−1.99***	(0.28)	−3.05***	(0.23)	−1.05***	(0.13)	−2.77***	(0.27)
Total	13.55***	(0.72)	12.97***	(0.54)	11.39***	(0.40)	13.45***	(0.44)	23.99	(0.89)
Specification error	4.88**	(1.69)	0.24	(0.97)	0.08	(0.75)	1.65	(1.25)	−3.43***	(2.17)
Pure wage structure effect										
Total	4.19	(6.38)	3.61	(4.00)	4.31	(3.15)	7.15	(5.04)	7.01	(9.00)
Reweighting error	2.36	(2.36)	1.63	(1.37)	0.57	(1.07)	0.07	(1.57)	−1.12	(2.77)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2008/09. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.8: Detailed decomposition results, 2012/13

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	27.64***	(0.91)	23.31***	(0.71)	19.08***	(0.49)	22.34***	(0.51)	24.95***	(0.78)
Pure composition effect										
Age	−0.99***	(0.16)	−1.06***	(0.17)	−0.57***	(0.09)	−0.27***	(0.04)	0.48***	(0.14)
Education	3.73***	(0.14)	4.47***	(0.18)	3.74***	(0.20)	5.52***	(0.36)	8.28***	(0.72)
Work experience	4.28***	(0.18)	5.61***	(0.23)	2.92***	(0.15)	0.64***	(0.06)	−0.11	(0.07)
Job tenure	0.76***	(0.07)	1.27***	(0.10)	1.18***	(0.09)	1.06***	(0.10)	0.48***	(0.04)
Collective bargaining	0.22**	(0.11)	0.22	(0.17)	0.06	(0.11)	0.06	(0.08)	−0.07	(0.06)
Plant size	−1.23**	(0.53)	−0.74**	(0.31)	−0.51**	(0.19)	−0.25	(0.023)	−0.37	(0.28)
Occupation	1.99***	(0.21)	3.84***	(0.21)	4.63***	(0.19)	6.46***	(0.26)	12.41***	(0.73)
Sector	5.93***	(0.27)	5.88***	(0.22)	3.45***	(0.20)	1.62***	(0.20)	1.00***	(0.28)
Foreign share	1.87***	(0.12)	1.38***	(0.17)	−1.20***	(0.20)	−0.25	(0.15)	0.63*	(0.32)
Region	−2.11***	(0.20)	−2.09***	(0.21)	0.55***	(0.20)	−0.56**	(0.23)	−0.89***	(0.43)
Total	14.44***	(0.54)	18.76***	(0.54)	14.26***	(0.51)	14.02***	(0.63)	21.84***	(1.15)
Specification error	7.84***	(1.87)	0.98	(1.20)	−0.78	(0.91)	2.59*	(1.36)	−1.60	(2.71)
Pure wage structure effect										
Total	2.42	(5.86)	1.59	(3.54)	4.12	(3.01)	6.19	(4.37)	6.73	(7.22)
Reweighting error	2.94	(2.41)	1.97	(1.47)	1.47	(1.25)	−0.46	(1.67)	−2.03	(2.88)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2012/13. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.9: Detailed decomposition results, 2016/17

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	26.62***	(0.71)	29.14***	(0.62)	27.25***	(0.57)	24.78***	(0.57)	25.29***	(0.75)
Pure composition effect										
Age	−0.04**	(0.02)	−0.16***	(0.05)	−0.21***	(0.08)	−0.04	(0.05)	0.22**	(0.09)
Education	1.95***	(0.07)	2.66***	(0.09)	3.06***	(0.15)	4.43***	(0.27)	6.51***	(0.44)
Work experience	3.89***	(0.13)	6.63***	(0.16)	6.11***	(0.16)	2.81***	(0.10)	1.75***	(0.11)
Job tenure	1.47***	(0.07)	2.04***	(0.08)	3.14***	(0.11)	3.48***	(0.12)	2.24***	(0.10)
Collective bargaining	0.20***	(0.03)	0.21***	(0.07)	0.02	(0.08)	0.00	(0.00)	0.12***	(0.04)
Plant size	0.20	(0.03)	−0.20	(0.20)	0.05	(0.23)	0.56**	(0.26)	0.42*	(0.22)
Occupation	2.18***	(0.16)	3.03***	(0.14)	5.09***	(0.16)	7.71***	(0.23)	12.78***	(0.48)
Sector	3.57***	(0.18)	5.80***	(0.18)	6.06***	(0.22)	2.58***	(0.32)	0.42	(0.60)
Foreign share	2.01***	(0.15)	2.23***	(0.22)	−1.00***	(0.11)	−0.64***	(0.06)	−0.43***	(0.06)
Region	−2.97***	(0.21)	−2.95***	(0.27)	0.14	(0.14)	−0.22	(0.16)	0.07	(0.19)
Total	11.98***	(0.33)	19.30***	(0.37)	22.48***	(0.45)	20.68***	(0.50)	24.11***	(0.76)
Specification error	9.25***	(2.00)	4.32***	(1.37)	−0.41	(1.03)	−2.31	(1.30)	−5.37**	(2.14)
Pure wage structure effect										
Total	3.47	(4.85)	4.07	(4.02)	4.90	(3.20)	7.36	(4.02)	6.91	(6.91)
Reweighting error	1.91	(2.60)	1.44	(1.75)	0.29	(1.34)	−0.96	(1.56)	−0.36	(2.41)

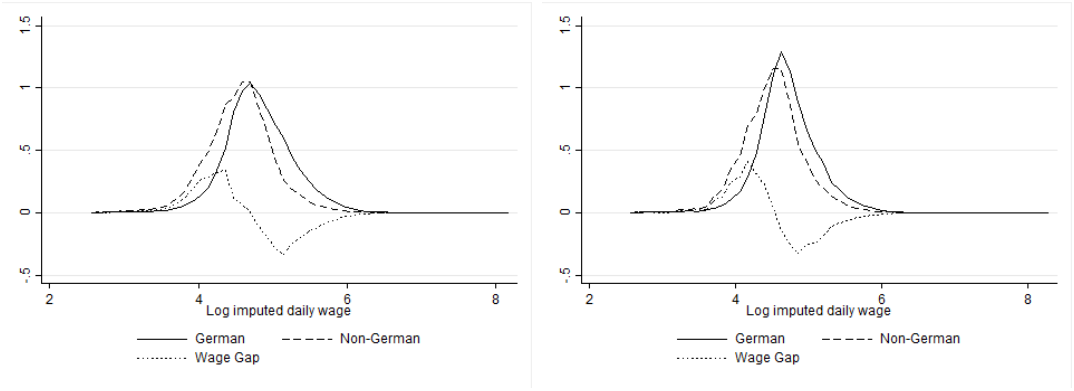
Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2016/17. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table A.10: Detailed decomposition results, 2018/19

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Std Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.	Coefficient	Std. Dev.
Log wage gap	24.08***	(0.70)	26.90***	(0.61)	26.45***	(0.57)	26.56***	(0.53)	27.77***	(0.76)
Pure composition effect										
Age	−0.07**	(0.03)	−0.06	(0.05)	−0.08	(0.08)	0.10*	(0.06)	0.29***	(0.08)
Education	2.18***	(0.09)	2.52***	(0.10)	3.09***	(0.18)	3.49***	(0.33)	5.34***	(0.59)
Work experience	4.68***	(0.16)	6.28***	(0.16)	6.85***	(0.18)	3.28***	(0.14)	1.87***	(012)
Job tenure	1.91***	(0.10)	2.69***	(0.11)	4.40***	(0.15)	4.63***	(0.16)	3.91***	(0.15)
Collective bargaining	0.05**	(0.02)	0.21***	(0.06)	0.37***	(0.12)	0.19***	(0.06)	0.31***	(0.09)
Plant size	−0.46***	(0.16)	−0.29	(0.21)	−0.01***	(0.30)	0.84***	(0.30)	1.55***	(0.28)
Occupation	1.74***	(0.16)	3.36***	(0.16)	4.76***	(0.17)	7.67***	(0.25)	13.99***	(0.64)
Sector	4.14***	(0.15)	4.26***	(0.15)	4.47***	(0.17)	1.66***	(0.20)	−0.44	(0.29)
Foreign share	0.64***	(0.14)	1.00***	(0.15)	−1.78***	(0.21)	−0.73***	(0.08)	−0.19***	(0.06)
Region	−1.66***	(0.22)	−2.59***	(0.23)	0.70***	(0.21)	−0.04	(0.12)	−0.20	(0.15)
Total	13.15***	(0.30)	17.38***	(0.35)	22.77***	(0.48)	21.10***	(0.52)	26.43***	()
Specification error	4.83	(3.24)	5.21***	(1.27)	−1.45	(1.09)	−2.28*	(1.32)	−5.57**	(2.41)
Pure wage structure effect										
Total	3.77	(7.00)	2.74	(3.27)	4.71	(0.50)	8.69	(3.83)	8.54	(6.36)
Reweighting error	2.34	(4.21)	1.59	(1.87)	0.50	(1.57)	8.69	(3.83)	−1.62	(3.10)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The table presents the results of the RIF-regressions based OB decomposition approach based on log daily wages for all considered percentiles in 2018/19. All coefficients above are multiplied by 100 for convenience. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

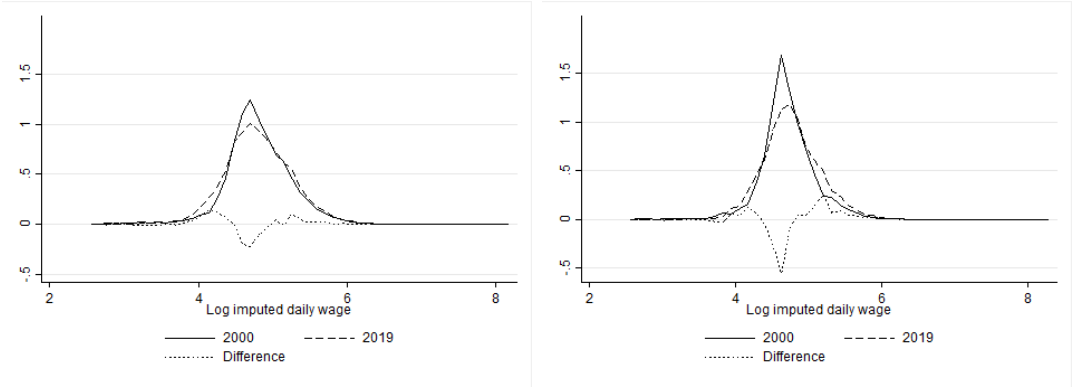
Appendix B



(a) Metropolitan regions (b) Non-Metropolitan regions

Figure B1: Wage densities by nationality, by region

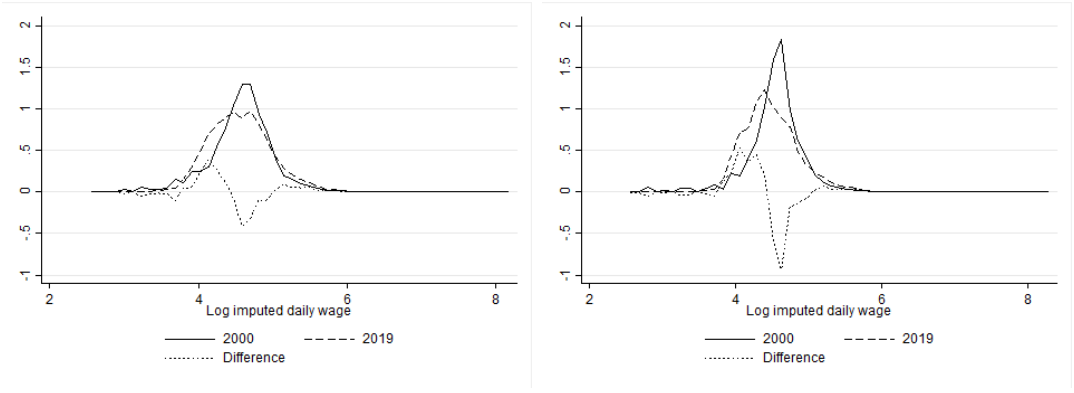
Source: LIAB QM2 9319, own calculations.
Note: The figure presents the kernel density estimations of the wage densities for workers in Metropolitan and Non-Metropolitan regions between 2000 and 2019. Sampling weights are employed.



(a) Metropolitan regions (b) Non-Metropolitan regions

Figure B2: Wage densities over time, German workers

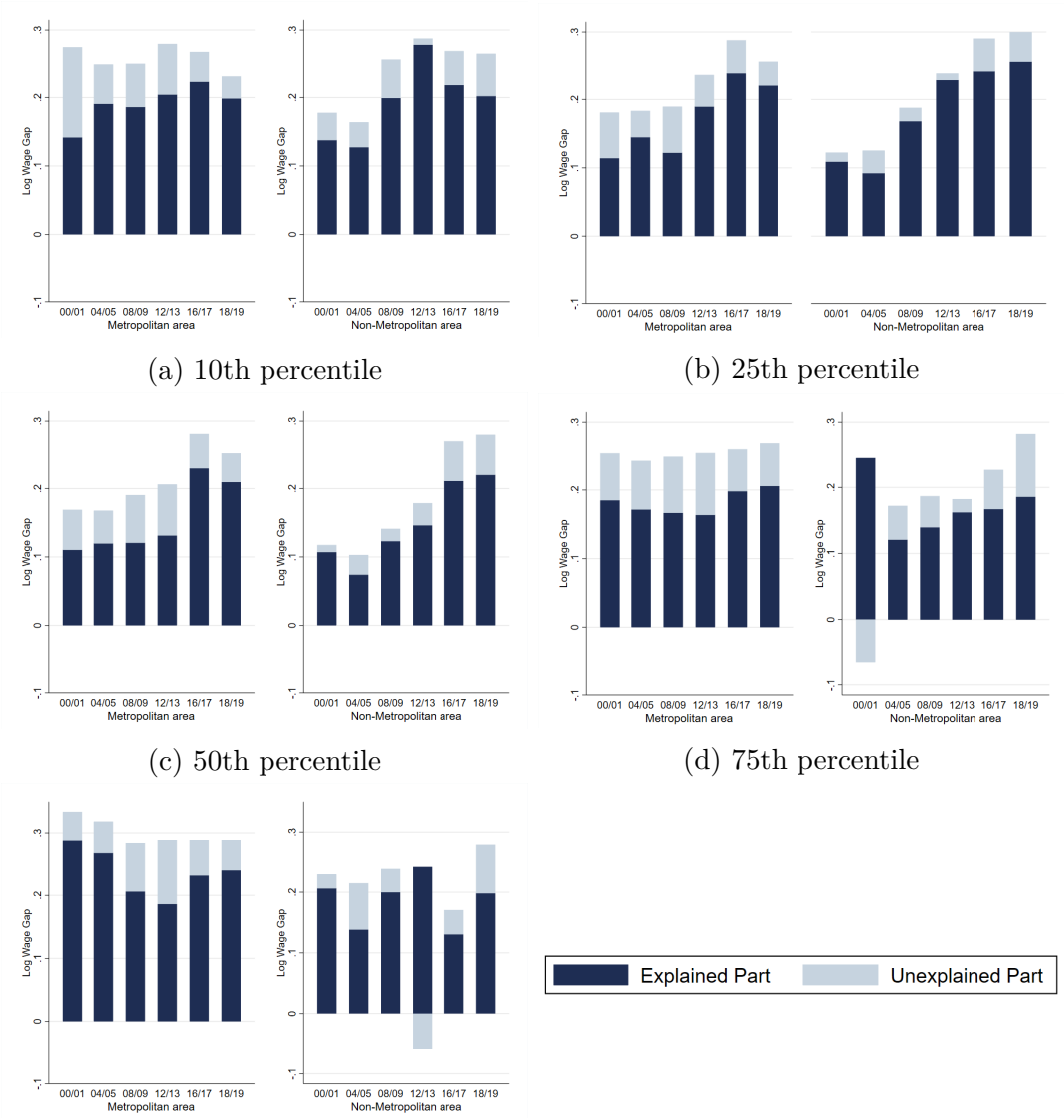
Source: LIAB QM2 9319, own calculations.
Note: The figure presents the kernel density estimations of the wage densities for German workers in Metropolitan and Non-Metropolitan regions for 2000 and 2019. Sampling weights are employed.



(a) Metropolitan regions (b) Non-Metropolitan regions

Figure B3: Wage densities over time, Non-German workers

Source: LIAB QM2 9319, own calculations.
Note: The figure presents the kernel density estimations of the wage densities for Non-German workers in Metropolitan and Non-Metropolitan regions for 2000 and 2019. Sampling weights are employed.



(a) 10th percentile

(b) 25th percentile

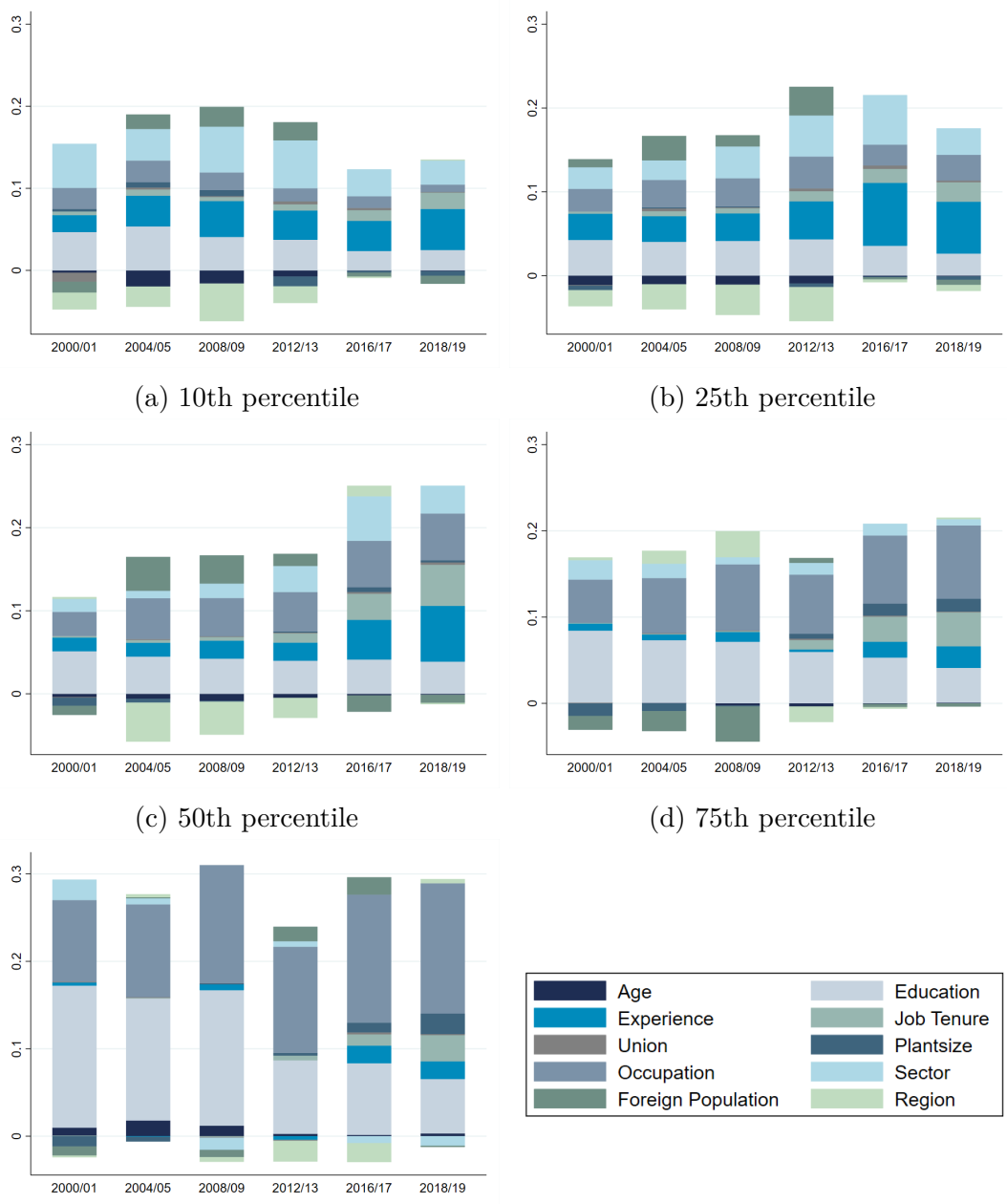
(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure B4: Aggregate decomposition of immigrant-native wage gaps along the wage distribution by region, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The different subfigures present the estimated results of the RIF-regressions based aggregate OB decompositions in metropolitan and non-metropolitan areas. Sampling weights are employed.



(a) 10th percentile

(b) 25th percentile

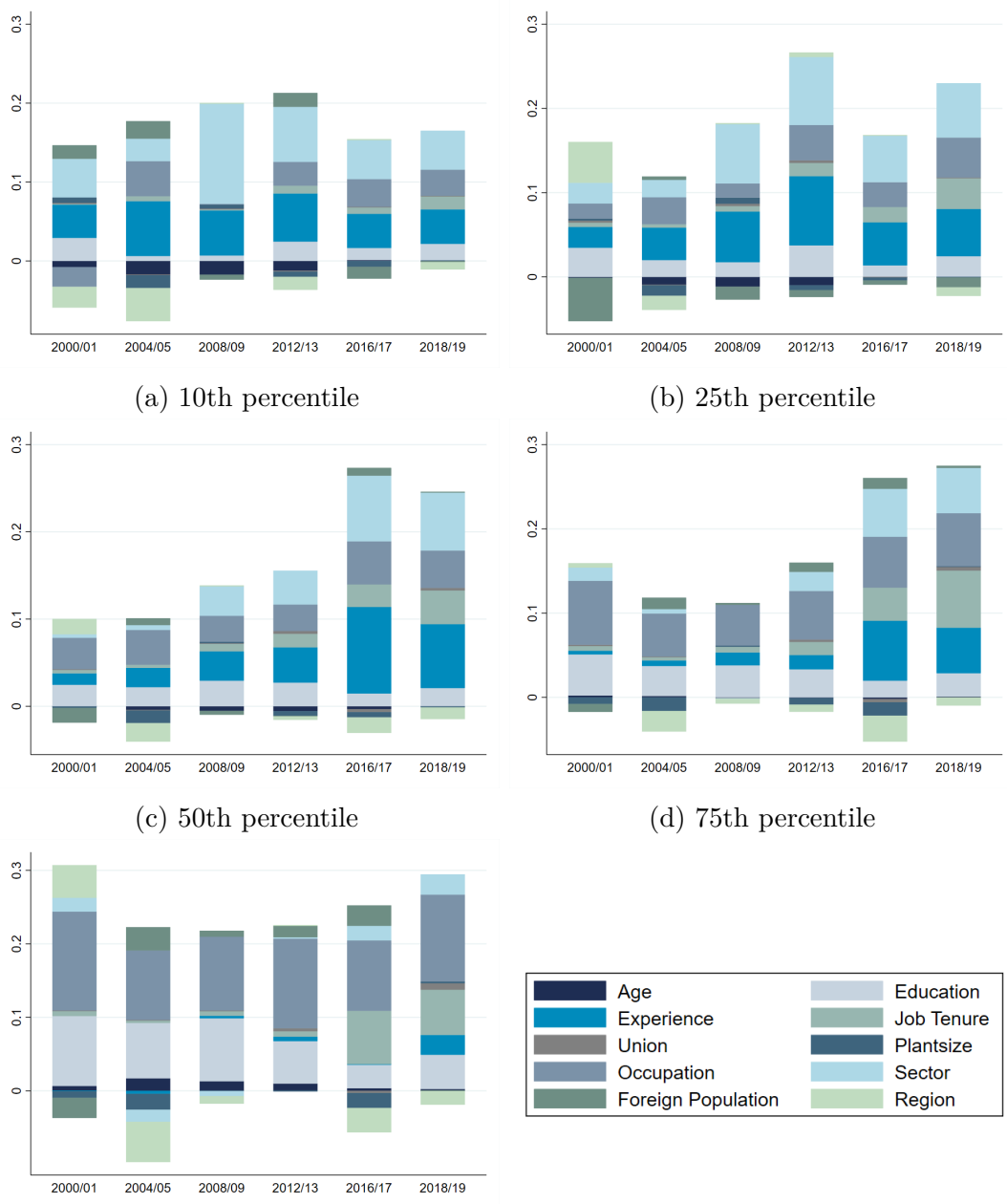
(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure B5: Detailed decomposition of the explained part in metropolitan areas, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The different subfigures present the estimated results of the RIF-regressions based detailed OB decompositions in metropolitan areas. Sampling weights are employed.



(a) 10th percentile

(b) 25th percentile

(c) 50th percentile

(d) 75th percentile

(e) 90th percentile

Figure B6: Detailed decomposition of the explained part in non-metropolitan areas, 2000-2019

Source: LIAB QM2 9319 and Federal Bureau of Statistics (Destatis) (2021a), own calculations.
Notes: The different subfigures present the estimated results of the RIF-regressions based detailed OB decompositions in non-metropolitan areas. Sampling weights are employed.

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