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Migration and wage inequality: a detailed analysis for German metropolitan and non-metropolitan regions

Ramona Schmid[1]

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Abstract This study presents new evidence on immigrant-native wage gaps considering regional-specific differences 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. The applied extended version of the Oaxaca-Blinder decomposition method provides evidence on driving factors behind wage gaps along the entire wage distribution. Estimated results are presented not only for the whole of West Germany but also differentiated between metropolitan and non-metropolitan areas. On average, larger wage differentials are identified in metropolitan areas with at the same time a higher presence of foreign population. Detailed decompositions show that 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. Decisive explanatory variables in this context are the practised profession and the economic sector affiliation. Distinguishing between metropolitan and non-metropolitan areas, provides evidence that especially differences in educational attainment impact wage gaps in urban areas. Regarding the size of overall estimated wage gaps, after 2012 a reversal in trend and particular increasing tendencies around median wages are revealed.

Keywords Immigrant-native wage gap · Oaxaca-Blinder decomposition · Unconditional quantile regression · Ethnic clustering · Germany

JEL classification J15 · J31 · J61 · R23 · R58

✉ Ramona Schmid
Ramona.Schmid@uni-hohenheim.de

1 Institute of Economics, University of Hohenheim, 70593 Stuttgart, Germany

Migration und Lohnungleichheit: Eine detaillierte Analyse für Deutsche Metropol- und Nicht-Metropolregionen

Zusammenfassung Diese Studie präsentiert neue Erkenntnisse im Bereich der Löhnlücke zwischen einheimischen und ausländischen Beschäftigten in Deutschland unter Berücksichtigung regionaler Unterschiede zwischen 2000 und 2019. Unter Verwendung von Linked-Employer-Employee-Daten des Instituts für Arbeitsmarkt- und Berufsforschung werden unbedingte Quantilsregressionen geschätzt, um den Grad der Integration von ausländischen Beschäftigten im deutschen Arbeitsmarkt auf regionaler Ebene bewerten zu können. Die Ergebnisse der erweiterten Oaxaca-Blinder Zerlegungsmethode erbringen Nachweis über entscheidende Faktoren, die die Lohnlücke entlang der gesamten Verteilung beeinflussen. Ergebnisse werden nicht nur für Westdeutschland als Ganzes präsentiert, sondern es wird zusätzlich zwischen Metropolregionen und ländlichen Regionen unterschieden. Die Unterscheidung zwischen verschiedenen Regionen in Deutschland zeigt, dass im Durchschnitt höhere Lohnlücken in Metropolregionen erkennbar sind mit einem gleichzeitig höheren Anteil an ausländischer Bevölkerung. Zusätzlich ändert sich nicht nur der relative Einfluss bestimmter erklärender Variablen im Laufe der Zeit, sondern auch mögliche Faktoren der Lohnlücke haben unterschiedlichen Auswirkungen an verschiedenen Stellen der Lohnverteilung. Entscheidende Faktoren in diesem Zusammenhang sind der ausgeübte Beruf und die Zugehörigkeit zu einem bestimmten Wirtschaftssektor. Bei der getrennten Beobachtung von Metropolregionen und ländlichen Regionen zeigt sich, dass vor allem Unterschiede in der Bildung zu Lohnlücken in städtischen Regionen führen. Hinsichtlich des Ausmaßes der Lohnlücken zwischen ausländischen und einheimischen Beschäftigten ist in den Jahren nach 2012 eine Trendumkehr zu erkennen, die mit einem Anstieg im Bereich der Medianlöhne verbunden ist.

Schlüsselwörter Lohngefälle zwischen Einheimischen und Zuwanderern · Oaxaca-Blinder Zerlegung · Unbedingte Quantilsregression · Ethnische Gruppierung · Deutschland

1 Introduction

After 2015, Germany was the second largest single destination country for international migrants among OECD countries behind the United States (OECD 2019). In this context, the Eastern enlargement of the EU, the financial crisis in 2008/09 and the 2015 refugee crisis play decisive roles for migration flows to Germany. At the same time, Germany is confronted with growing labour shortages in high- and medium-skilled occupations due to its shrinking working-age population. Managed labour migration is therefore an additional factor of increasing foreign workforce in order to match labour demands (OECD 2018). Depending on the area of settlement, foreign workers are confronted with regional-specific labor market conditions. In the presence of urban-rural wage gaps (Brixy et al. 2022) and higher shares of foreign population in German metropolitan areas (Schaffner and Treude 2014; Glitz 2014), it is of special interest to analyse wage differentials between German and Non-German workers within a regional context of metropolitan and non-metropolitan areas. The extent of immigrant-native wage gaps provides insights on how well foreign workers are integrated into the labor market and society. Thus, analyzing overall wage gaps between German and Non-German workers but also possible differences depending on the area of work is of particular importance and make Germany to a special case. Detailed analyses of driving factors and developments of wage differentials not only over time but also in different regions are thus of high relevance for decisions in immigration and labor market policies (Ingwersen and Thomsen 2021; Brunow and Jost 2022).

This paper adds to current literature evidence on developments of wage differentials between German and Non-German workers with a special focus on regional differences between German metropolitan and non-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. Therefore, it is identified how the impact of various explanatory factors on wage differentials evolves over time. Additionally, until now not considered possible effects resulting from changes in the share of foreign population are observed.

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 the presentation of regional-specific variation in the magnitude of wage gaps. On average, higher immigrant-native wage differentials are estimated in large cities and metropolitan areas. At the same time, tendencies of ethnic clustering in these areas are identified.

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. With a focus on the part of wage gaps that is explainable by differences in the observable characteristics between German and Non-German workers, the study provides insights on the driving factors behind the endowment effect. There is not only evidence for changes in the relative importance 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. Based on these analyses, regional-specific decomposition analyses in metropolitan and non-metropolitan areas contribute evidence on varying impact of characteristics explaining wage gaps. In particular, differences in educational levels play a crucial part in explaining higher wage gaps in urban areas.

The remainder of this paper proceeds as follows: Sect. 2 provides an overview on related literature. In Sect. 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 Sect. 4. Further, in Sect. 5 the empirical approaches are specified and finally, the empirical results are presented in Sect. 6. Discussion and conclusion of the estimated findings are provided in Sect. 7.

2 Related Literature

General literature on immigrant-native wage differentials. 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 considerably 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 German 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. Focusing on differences regarding the country of origin, where administrative data is used, Brunow and Jost (2021) show distinct country-specific variation in wage gaps between German and Non-German workers that should be taken into account in managed migration considerations. In applied Oaxaca-Blinder decompositions, Brunow and Jost (2022) then identify that wage gaps mainly result from differences in observable characteristics, such as the location, labor market experience and firm characteristics. Further, they conclude that Non-German workers receive equal remuneration and possible discrimination is insignificant in this context. The study by Ingwersen and Thomsen (2021), 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 for 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.

Literature on regional consequences of immigration. 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 (2012a) 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 leads 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. With the focus on metropolitan areas, Ottaviano and Peri (2012b) show a positive and significant relationship between the increase of foreign workers and changes in the average wage of natives across US metropolitan areas. Distinguishing this 'area analysis' approach between educational levels, larger positive wage effects on highly educated natives and a small negative effect on the wages of less educated natives are revealed.

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 2021)a. The literature provides evidence that ethnic clustering

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

plays a non-negligible role in the decision of residence for foreign born workers in Germany (see for example Schaffner and Treude 2014 and Glitz 2014). 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. Due to evidence of a higher presence of foreign born population in metropolitan areas and the described possible consequences of ethnic clustering, the following analysis seeks in revealing differences in the size of wage differentials. Thus, 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 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

[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. https://doi.org/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).

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. At the same time, the analysis is restricted to full-time workers. It could be assumed that the observed Non-German workers are potentially well-integrated into the German labor market and should represent less marginalized groups that are forced to work in certain sectors or conduct particular occupational tasks.[3] Further studies with similar design and reasoning regarding the definition of the main variable are, for example, Brunow and Jost (2022) and Ohlert et al. (2016).

The empirical analysis considers male workers between 25 and 55 years[4], who earned more than 10 Euros per day between 2000 and 2019.[5] 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 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

[3] When it comes to analyzing immigrant-native wage differentials among full-time employed workers, it should be kept in mind that for part-time employed workers the situation might be even more disadvantageous. However, due to the data design, with no available detailed information on working hours, an analogous analysis for part-time employed workers is not feasible.

[4] 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.

[5] In order to exclude extreme outliers of daily wages, especially for the period before the introduction of the statutory hourly minimum wage in 2015, observations with a daily wage below 10 Euros are left aside.

wage setting processes.[6] 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 2021)a.[7] Thus, it is possible to match this data set with the administrative labor market data using the variable indicating the district of employment.[8] 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).[9] 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).[10]

The observed time span of the analyses covers the years from 2000 to 2019.[11] Further, in order to circumvent possible outliers and reduce the dependency on specific years, the decomposition analyses are based on pooled time points.[12] Regarding the regional aspect of the study, this approach as well guarantees a sufficient sample size for each observed time point and increases variation. In order to get an impression how immigrant-native wage gaps and the driving forces develop over time, the time points are equally distributed along the period of observation.

Variables under consideration. The following analyses consider individual explanatory factors that are represented by the age and its square as well as the educational level of workers (three dummy variables[13]). Regarding the individual work experience, the days in employment and the days of job tenure as well as their

[6] Since there are considerable differences in the level of pay between the East and the West of Germany, this decision follows common procedure in the literature using this type of data (see Dustmann et al. 2009, Biewen and Seckler 2019 and Baumgarten et al. 2020).

[7] Between 2000 and 2019 there are several changes in the composition of districts. The major changes are listed in Table in 2 in Appendix A. The respective merged districts are considered as one district over the whole period of observation.

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

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

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

[11] Due to data availability reasons of the data coming from the German Federal Office of Statistics and the specification of the conducted robustness checks provided in Appendix C, the earliest possible starting year is 2000.

[12] A similar procedure can be seen for example in Biewen and Juhasz (2012) and Biewen et al. (2019).

[13] (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.

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) and the firm size (six dummy variables[14]) augment the explanatory factors. Since the general decline of collective bargaining coverage in Germany is a discussed topic regarding the overall development of wage inequality[15] information on the bargaining regime (three groups[16]) is added as well. Regional-specific effects are controlled by the share of foreign population and dummy variables indicating ROR-regions. For the separate decomposition analyses for metropolitan and non-metropolitan areas the list of the ROR-region-dummies is adjusted accordingly to the underlying regions.

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.

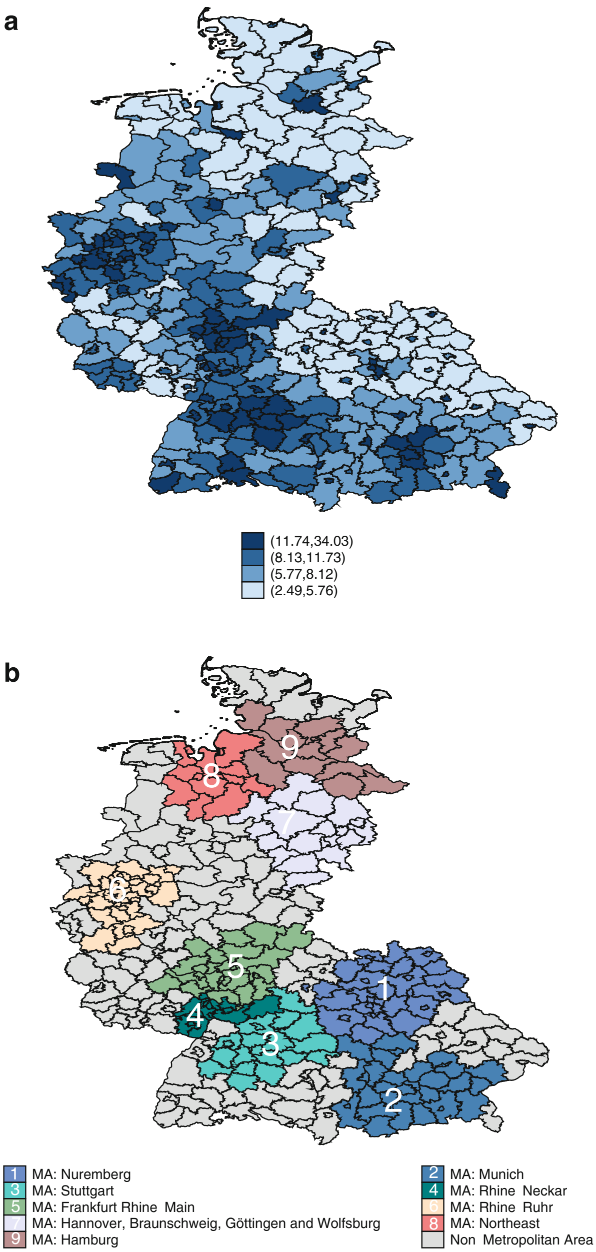
Immigration and regional differences. Due to several migration flows after the Second World War, Germany exhibits today a society with several nations and cultures of different regions from all over the world. Starting with the targeted recruitment of the so-called guest-workers in the 1950s, workers 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, led 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 2021)a. Of course, this development is referable to the significant inflow of migrants coming from Eastern but also from Southern Europe. After the global financial crisis in 2008/2009, unemployment rates increased in counties like Italy, Greece and Spain resulting in a rise of skilled labour inflow (Seibert and Wapler 2020). With the begin of the refugee crisis in 2014/15 once again new immigrants arrived in Germany leading to an overall heterogeneous migrant population. 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

[14] (1) 1–9 employees; (2) 10–49 employees; (3) 50–199 employees; (4) 200–999 employees; (5) 1000–4999 employees; (6) $\geq$ 5000 employees.

[15] See for example Baumgarten et al. (2020) and Felbermayr et al. (2014).

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

Fig. 1 Regional differences **a** Share of the foreign population in West Germany, 2000–2019, **b** Metropolitan areas in West Germany (*Source*: **a** Federal Bureau of Statistics (2021)a, **b** Kawka (2016), own depiction. *Note*: **a** presents the share of the foreign population at the level of administrative districts in West Germany for 2000 to 2019. **b** presents metropolitan areas in West Germany defined by the Initiative Circle European Metropolitan Regions in Germany (2022).)



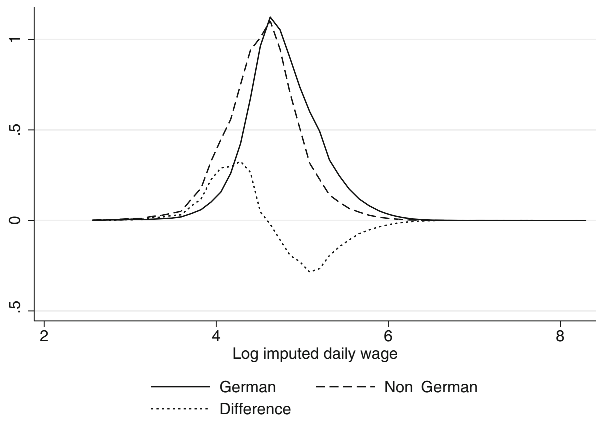


Fig. 2 Wage densities, 2000–2019 (*Source*: LIAB QM2 9319, own calculations. *Note*: The figure presents kernel density estimations of wage densities for German and Non-German workers between 2000 and 2019. Sampling weights are employed.)

of the Middle East and Asia, such as Syria, Afghanistan and Iraq (Federal Bureau of Statistics 2021)b.

Having a closer look at the regional settlement of the foreign population in West-Germany, Fig. 1a 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.

Fig. 1b presents metropolitan regions of West Germany defined by the Initiative Circle European Metropolitan Regions in Germany (2022) in 2008 (Kawka 2016).[17] The concept of European Metropolitan Regions was introduced in the mid-1990s as a program of social, economical and cultural advancement aiming to support the international performance and competitiveness of Germany.[18] Comparing these areas with the observed ethnic clusters of Fig. 1a, it is shown that migrants tend to settle down in larger cities and economically prospering regions.[19] Especially, the areas Rhine-Ruhr, Frankfurt Rhine-Main, Stuttgart and Munich reveal a high level of this relationship.

As a result, the underlying observed presence of a higher fraction of foreign population in metropolitan areas is supported. Thus, one can conclude that clustering is an observable factor in Germany that should be examined further, especially in the context of wage differences between Germany 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, Fig. 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

[17] In total, there are 11 metropolitan areas in Germany (Initiative Circle European Metropolitan Regions in Germany 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.

[18] For further details see Michel (1998), Rusche and Oberst (2010) and Diller and Eichhorn (2022).

[19] These findings are in line with Schaffner and Treude (2014), Glitz (2014) and Winke (2018).

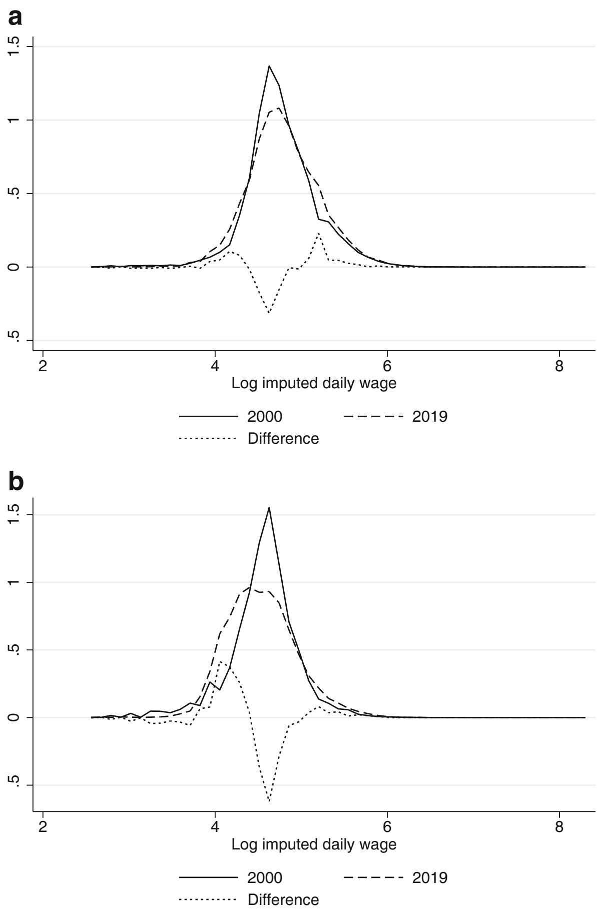
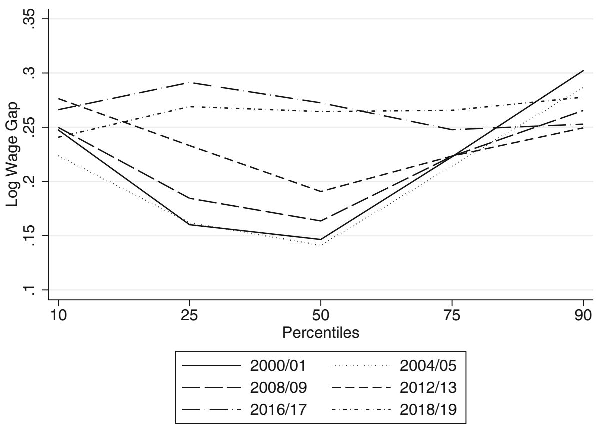


Fig. 3 Change in wage densities over time **a** German workers, **b** Non-German workers (*Source*: LIAB QM2 9319, own calculations. *Note*: The figures present kernel density estimations of wage densities for German **(a)** and Non-German **(b)** workers in comparison for the years 2000 and 2019. Sampling weights are employed.)

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.

Since this study seeks in providing evidence on changes in wage differentials over time, Fig. 3 shows the wage densities separately for German and Non-German workers for the years 2000 and 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 between the two groups of workers is identified. On the one side, in subfigure a more mass is shifted to the right of the distribution, indicating an increase of German workers in higher paid jobs, which is depicted by the difference between the two densities. On the other side, subfigure b shows for Non-German workers a higher difference between 2019 and 2000 at the lower half of the wage distribution. Thus, substantial

Fig. 4 Log wage gaps by percentiles, 2000–2019 (*Source*: LIAB QM2 9319, own calculations. *Note*: The Figure presents wage gaps between German and Non-German workers by percentiles (10, 25, 50, 75, 90) between 2000 and 2019. Sampling weights are employed.)



differences in the allocation of workers along the wage distribution, that change over time and are influenced by the widening of the group's wage distributions, are identified.

Going into more detail how wage differentials evolve over time at different points of the wage distribution, Fig. 4 presents raw wage gaps between German and foreign workers for the 10th, 25th, 50th, 75th and 90th percentiles over time. 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.

Since this study seeks in providing evidence on differences between metropolitan and non-metropolitan areas, Fig. 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 Fig. 1b. Especially, the regions around Hamburg, Bremen, Frankfurt Rhine-Main, Stuttgart, Munich and Nuremberg exhibit the highest observed wage gaps. The estimated correlation between the fraction of foreign population and the value of the estimated mean wage gaps between German and Non-German workers is moderate positive with the value 0.45. In addition, this relationship is supported by kernel density estimations in Figs. 9–11 in Appendix B, where a higher wage dispersion and a larger shift between German and Non-German workers are presented in metropolitan regions.[20]

[20] Table 3 in Appendix A reveals not only significant differences in immigrant-native wage gaps between metropolitan and non-metropolitan areas but also supports evidence on substantial urban-rural wage differentials in Germany as recently analyzed by Brixy et al. (2022). In general, the existing literature provides results on wage advantages for workers in large urban areas (see for example Yankow 2006; Gould 2007; Heuermann et al. 2010).

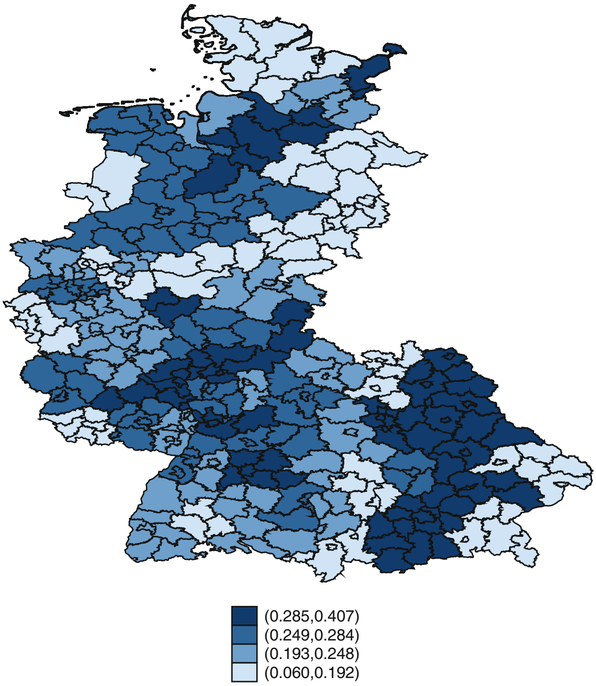


Fig. 5 Wage differentials between German and Non-German workers, by regions (*Source*: LIAB QM2 9319, own calculations. *Note*: The Figure presents the wage differentials at the mean between German and Non-German workers at the level of ROR-regions in West Germany, 2000–2019.)

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

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.[21] 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. A crucial factor when it comes to explaining immigrant-native wage differentials is the level of observed educational attainment. For Non-German workers, the share of the lowest educational group 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 80% for German workers and 60% 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

[21] In order to present clear descriptive statistics, Table 1 presents only the selected points in time 2000/01, 2008/09 and 2018/19. Thus, the general trend of changes in the characteristics from the beginning of the observed time period via the middle of the period (2008/09) until the end of observation time can be identified.

Table 1 Descriptive statistics; 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
Individual characteristics						
Age:	39.69	38.22	41.55	39.49	41.34	40.14
Education:						
Low	5.35	33.80	4.45	27.88	3.76	20.86
Middle	80.12	60.12	78.29	61.68	76.53	64.94
High	14.52	6.82	17.26	10.44	19.70	14.19
Days in employment:	5357.09	4359.11	6311.28	4885.39	6339.73	3922.65
Job tenure (days):	2753.02	2344.02	3258.02	2743.82	3013.37	1875.20
Firm-specific characteristics						
Collective bargaining regime:						
No collective agreement	24.22	23.59	32.27	33.38	40.19	44.22
Firm level agreement	7.84	5.89	9.87	8.97	9.93	9.41
Sector level agreement	67.93	70.51	57.86	57.66	49.88	46.37
Plant size:						
Number of employees	1043.76	1390.41	1256.25	1307.73	1262.47	851.80
Regional-specific characteristics						
Share of foreign population:	10.17	11.93	9.15	10.77	13.85	15.13
Metropolitan area:	65.19	71.99	64.85	73.79	63.48	68.96
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 (2021)a, own calculations.
Notes: The table presents descriptive statistics for specific variables in the selected points in time 2000/01, 2008/09 and 2018/19. The educational level of workers is represented by three dummy variables: (1) Low – lower/middle secondary without vocational training; (2) Medium – lower/middle secondary with vocational training or upper secondary with or without vocational training and (3) High – university of applied sciences or traditional university. The bargaining regime is defined by three groups: (1) Sector-level agreement; (2) Firm-level agreement; (3) No collective bargaining agreement. The shares are multiplied by 100 for convenience. Sampling weights are employed.

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 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. In Table 1 also the overall numbers of observations for selected time points are given.[22]

5 Empirical Approach

The empirical analyses combine different estimation strategies in order to provide estimates on the immigrant-native wage differentials and its driving factors for overall West-Germany but also at the level of metropolitan and non-metropolitan areas.

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 recentered influence functions (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, $\mathrm{IF}(w; v)$, shows the 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 $\mathrm{RIF}(w; v)$ can be estimated:

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

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

Since subsequent analyses aim in estimating among others the effects of immigrant population on different parts of the wage distribution in different regions of Germany, 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)

[22] The noticeable decrease in the number of observations over time between 2000 and 2019 occurs due to an overall decrease of the data set size, which is documented by the Research Data Center of the IAB.

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[23], μ:

$$\widehat{\Delta}_O^{\mu} = \bar{w}_N - \bar{w}_F = \left(\bar{X}_N - \bar{X}_F\right)'\widehat{\beta}_F + \bar{X}_N' \left(\widehat{\beta}_N - \widehat{\beta}_F\right). \tag{2}$$

The first half of Eq. (2) denotes the explained part that is based on mean differences in covariates and is called composition effect. In this case, the characteristics of Germans and Non-Germans are valued by the coefficient of foreign workers. If Non-German workers have the same characteristics as German workers, the composition effect is zero. The second half represents the part that cannot be explained due to differences in explanatory factors. This wage structure effect defines the unexplained, residual part of the wage gap between German and Non-German workers. In other words, this part represents the value of how much better native workers are valued compared to their foreign counterparts (Fortin et al. 2011).[24]

Together with the estimated coefficients of unconditional quantile regressions, $\widehat{\gamma}_{g,\tau}$[25], for each group, where $g = N, F$, the OB decomposition of Eq. (2) at quantile τ is defined as:

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

where $\widehat{\Delta}_O^{\tau}$ 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.[26] 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.[27]

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

[24] In the following, the terms endowment effect and composition effect as well as wage structure effect and coefficient effect are used interchangeably.

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

[26] 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 $\bar{X}_N \widehat{\beta}_F$.

[27] The reweighting function is estimated as follows: $\widehat{\psi}_X(X) = \dfrac{Pr(g = F)}{Pr(g = N)} \dfrac{Pr(g = N|X)}{Pr(g = F|X)}$, $Pr(g = N)$ 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).

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:

$$\widehat{\Delta}^{\tau}_{X,R} = \left(\bar{X}_C - \bar{X}_F\right)' \widehat{\gamma}_{F,\tau} + \bar{X}'_C \left(\widehat{\gamma}_{C,\tau} - \widehat{\gamma}_{F,\tau}\right). \tag{4}$$

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:

$$\widehat{\Delta}^{\tau}_{S,R} = \bar{X}'_N \left(\widehat{\gamma}_{N,\tau} - \widehat{\gamma}_{C,\tau}\right) + \left(\bar{X}_N - \bar{X}_C\right)' \widehat{\gamma}_{C,\tau}. \tag{5}$$

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 $\text{plim}(\bar{X}_C) = \text{plim}(\bar{X}_N)$. This results in a reweighting error that goes to zero, if the reweighting factor $\widehat{\psi}(X)$ is consistently estimated.

In order to show the regional-specific aggregate and detailed decomposition results Eqs. (4) and (5) are adjusted accordingly for metropolitan and non-metropolitan areas. In this context, the dependent variables are the wages of German and Non-German workers either in the defined metropolitan regions of Fig. 1b or the remaining regions.

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 2022). 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.

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 two parts. On the one hand into an endowment effect that is explained by differences in characteristics and on the other hand 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. In advance to the analyses on regional differences between metropolitan and non-metropolitan areas, it is evident to have at first a look on the general developments in West Germany as a whole. On this basis, it is subsequently possible to compare the regional results to the baseline model and put them into relation. Fig. 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)[28]. 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 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

[28] 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.

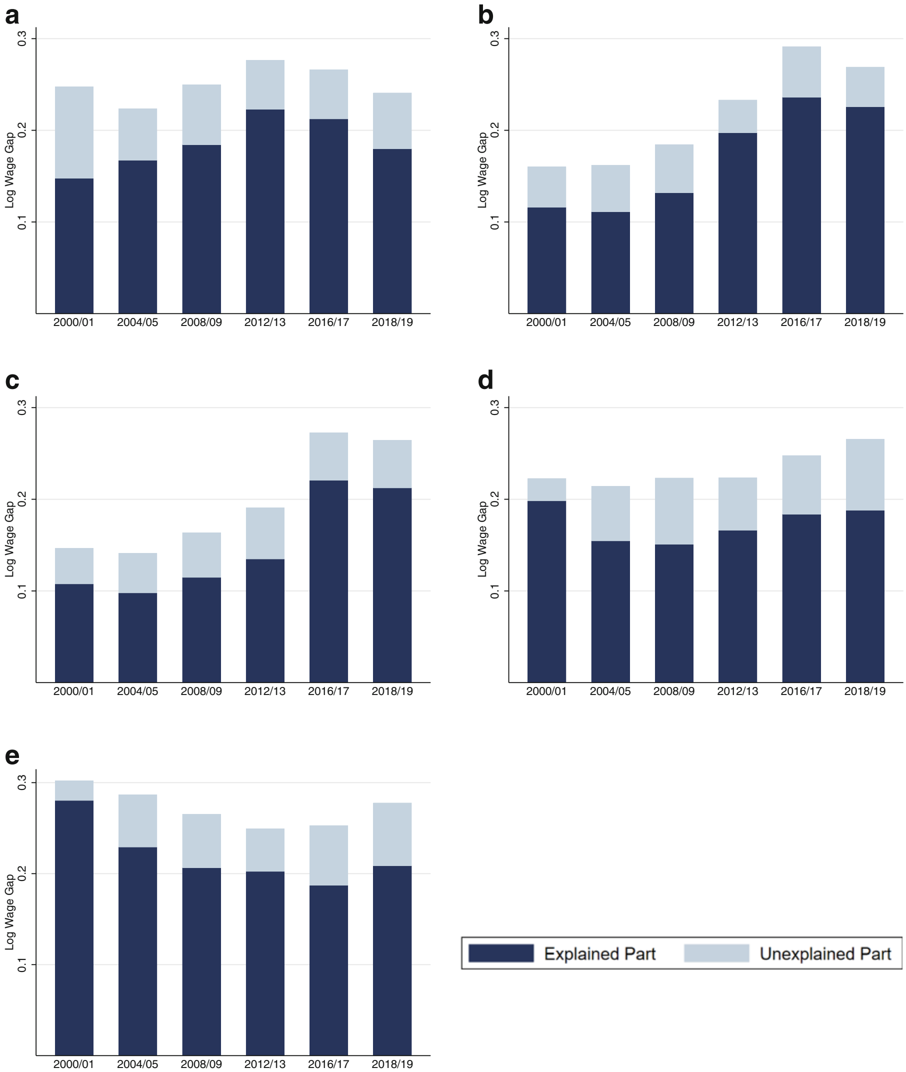


Fig. 6 Aggregate decomposition of immigrant-native wage gaps along the wage distribution, 2000–2019 **a** 10th percentile, **b** 25th percentile, **c** 50th percentile, **d** 75th percentile, **e** 90th percentile (*Source*: LIAB QM2 9319 and Federal Bureau of Statistics (2021)a, own calculations. *Notes*: The different subfigures present the estimated results of the RIF-regressions based aggregate OB decomposition. Sampling weights are employed.)

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[29] as well as on the other side between German workers and workers from the rest of the world. Tables 4 and 5 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, significantly lower shares of composition effects explaining wage differentials between Non-EU citizens and German workers are presented and thus evidence for possible discriminatory remuneration structures is presented. In this context, distinctions in the legal access of foreign workers to the German labor market have to be mentioned. In general, there is a substantially easier access for workers of EU countries compared to workers from the rest of the world. As a result of the European integration process, foreign EU-citizens have the same legal access to the German labor market as domestic individuals. In contrast to this, Non-EU workers are confronted by specific regulations and required permissions (see Brunow and Jost 2019; Dorn and Zweimueller 2021). Thus, regarding the extent of unexplained effects and resulting measures by policy makers, the observed group of foreign workers plays a decisive role.

Regional differences. Based upon the results above, it is possible to range in the regional aggregate decomposition results that are estimated separately for metropolitan and non-metropolitan areas (see Fig. 7).[30] Having a closer look at overall wage gaps in metropolitan areas, similar developments as seen before along the wage distribution are observed. The aggregate decomposition similarly provides significant evidence for larger fractions of unexplained parts at lower wages in the beginning of the observed time period. Moreover, in contrast to the overall results the effects that cannot be explained by differences in the observed characteristics are considerably present (around 35%) at the median and 75th percentile wage gaps until 2012/13. In contrast, at the highest wage gaps the unexplained part decreases over time and smaller values since 2016/17 are identified. The results for the defined non-metropolitan areas reveal on average the lowest values of wage differentials, especially between 2000/01 and 2012/13. Another striking difference compared to the estimates presented until now, are significantly lower values of unexplained effects. Until 2012/13, the effect that is not explainable by differences in characteristics is on average 13 percentage points higher in metropolitan than in non-metropolitan areas. Further, there is a general trend towards higher wage gaps at all parts of the wage

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

[30] In Tables 12 and 13 in Appendix A the aggregate decomposition results are presented.

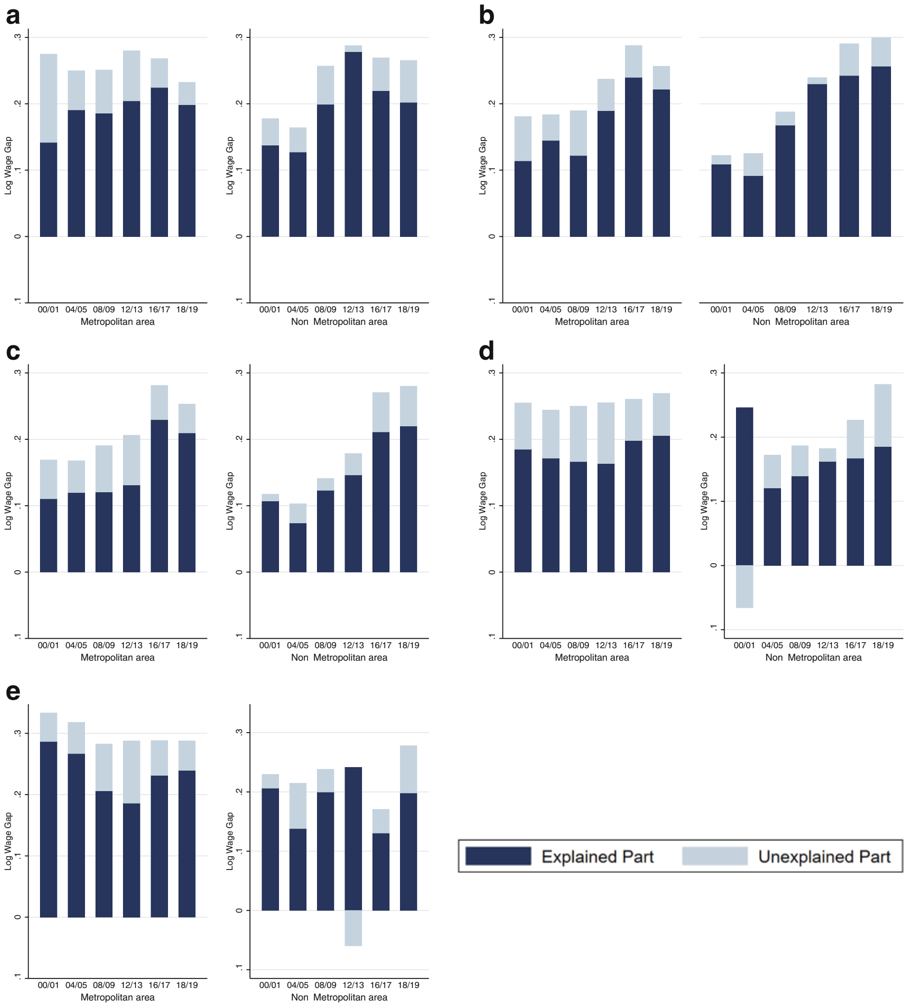


Fig. 7 Aggregate decomposition of immigrant-native wage gaps along the wage distribution by region, 2000–2019 **a** 10th percentile, **b** 25th percentile, **c** 50th percentile, **d** 75th percentile, **e** 90th percentile (*Source*: LIAB QM2 9319 and Federal Bureau of Statistics (2021)a, own calculations. *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.)

distribution revealed after 2012/13 for non-metropolitan areas. Thus, overall wage 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 mainly explain 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. Again, at first the general detailed decomposition estimates of endowment effects at different points of the wage distribution (10th, 25th, 50th, 75th and 90th percentile) over the time span of 20 years (2000–2019) are presented in Fig. 8.[31] Overall, 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 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.

[31] The detailed decomposition is conducted applying the proposed procedure by DiNardo et al. (1996), where at first a counterfactual distribution is estimated. Thus, in Fig. 8 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 6–11 in Appendix A.

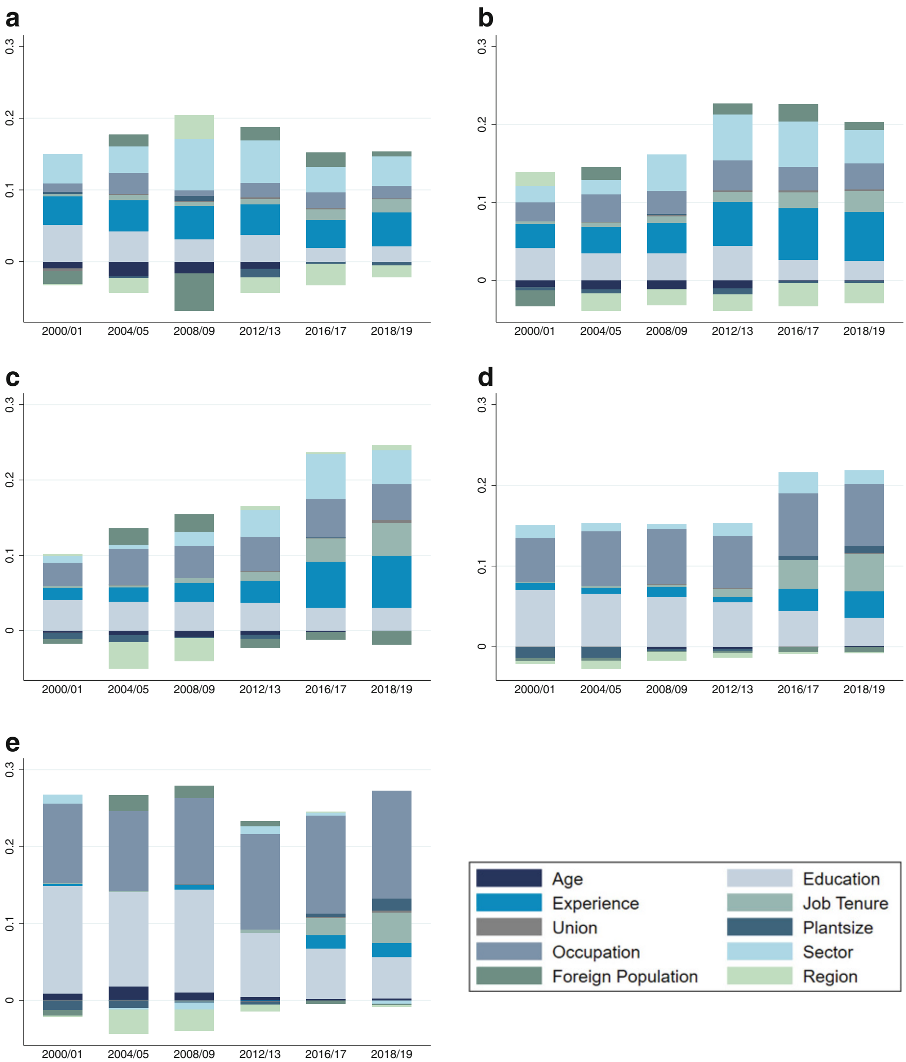


Fig. 8 Detailed decomposition of the explained part, 2000–2019 **a** 10th percentile, **b** 25th percentile, **c** 50th percentile, **d** 75th percentile, **e** 90th percentile (*Source*: LIAB QM2 9319 and Federal Bureau of Statistics (2021)a, own calculations. *Notes*: The different subfigures present the estimated results of the RIF-regressions based detailed OB decomposition. Sampling weights are employed.)

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.[32]

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. Regarding the latter explanatory variable no nationality-specific affiliation to a specific regime is observed, which could have impacted wage differentials between German and Non-German workers. 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.[33]

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. Figs. 12 and 13 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-

[32] In order to validate the estimated results on the effects due to the presence of foreign workforce, a respective robustness check is presented in Appendix C.

[33] In order to validate the results of the overall estimated effects of the different factors, a respective robustness check on pooled fixed effects is presented in Appendix C.

specific higher discrepancies between German and foreign workers in metropolitan areas in seeking for higher levels of education. Table 3 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 revealing a structural difference regarding educational attainment compared to non-metropolitan areas. 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.[34]

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.

7 Discussion and Conclusion

During the last years, Germany experienced noticeable increases in the share of 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. This development can be traced back to the significant influx of foreigners after 2015 and the relating thereto observed decrease in provided time of job tenure and experience. This increasing lack of job-specific knowledge of Non-German workers in comparison to their German counterparts therefore possibly leads to a different remuneration through the employers. As a result, overall wage gaps increase. Distinguishing between urban and rural areas, 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

[34] In order to validate the estimated results on the differences between metropolitan areas and non-metropolitan areas, respective robustness checks are presented in Appendix C.

identify 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 workers' remuneration. This striking development is supported by findings of Brunow and Jost (2021), 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.

When it comes to the 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.

Based on the estimations of the presented decomposition analyses several policy related implications addressing the driving forces behind wage differentials can be derived. The significant results regarding the wage gap increasing effects due to differences in the economic sector affiliation at the lowest wage levels and differences in the affiliation to occupations at higher wages emphasise policy measures dependent on the location along the wage distribution. Especially, with regard to the fact that the underlying study is restricted to possibly better in the labor market integrated full-time employed workers, these circumstances need to be addressed. Thus, policy programs should be developed in order to prevent forced selection of foreign workers into specific sectors and occupations conditional on the striven wage. The concerned sectors and occupational segments are in particular the manufacturing, hospitality and economic service sectors as well as jobs in production, logistics and cleansing. Especially regarding the observed trends towards sticky floors and glass ceiling in these areas focused action is appropriate. Another development that has to be mentioned is the striking increase of impact due to differences in experience and job tenure during the last years. It is identified that these factors play a decisive role explaining wage differences and thus policy should provide a course of action to reduce these possible insecurities regarding the lack of work experience in Germany. Relating thereto, in view of considerable lack of specialists and an aging population with a loss of labor force of around several hundred thousands each year, immigration is essential for the German labor market (Kaltwasser and Schludi 2022; Fuchs and Weber 2018 and Sauer and Wollmershäuser 2021). Policies that provide enhanced processes of paperwork in German immigration authorities as well as uncomplicated recognition of foreign certificates and diplomas are required. In this context, the results of the regional-specific analyses are crucial. Since significantly larger effects due to differences in educational levels in metropolitan areas are identified, aimed policy measures are required. These actions should enable structural conditions in which a more equal distribution of educational attainment is achieved. In addition, the literature shows that it is crucial for the economic future of cities to attract young and qualified workers (see Buch et al. 2014; Kühn 2018; Facchini and Lodigiani 2014). In the face of substantial skills shortage and striven managed migration for labour force compensation, these implications gain in relevance once more. Attracting additional workforce from abroad requires thus at the same time political measures ensuring an appropriate integration in different regional labor markets in Germany.

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

8 Appendix

8.1 Appendix A

Table 2 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 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 3 Additional descriptive statistics; 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
Non-metropolitan area	119.91	100.00	117.95	96.81	126.01	95.69
Individual characteristics						
Education:						
Low						
Metropolitan area	5.16	34.38	4.40	27.73	3.82	20.10
Non-metropolitan area	5.71	32.32	4.55	28.33	3.82	20.10
Middle						
Metropolitan area	78.51	58.90	76.09	61.04	74.35	64.47
Non-metropolitan area	83.14	63.26	82.36	63.48	80.32	65.95
High						
Metropolitan area	16.33	6.73	19.52	11.24	21.83	15.41
Non-metropolitan area	11.15	4.42	13.09	8.19	16.02	11.50
Regional-specific characteristics						
Share of foreign population:						
Metropolitan area	12.01	13.57	10.47	11.87	15.38	16.60
Non-metropolitan area	6.79	7.85	6.63	7.42	11.51	12.17

Source: LIAB QM2 9319 and Federal Bureau of Statistics (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 4 Aggregate decomposition results, German and EU workers

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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)
Log wage gap	27.51***	(0.89)	32.70***	(0.75)	32.68***	(0.81)	27.97***	(1.01)	21.43***	(1.21)

Table 4 (Continued)

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 5 Aggregate decomposition results, German and Non-EU workers

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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***	(3.43)
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)
Log wage gap	25.46***	(1.08)	22.92***	(0.86)	20.92***	(0.77)	22.59***	(0.60)	29.11***	(0.86)

Table 5 (Continued)

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 6 Detailed decomposition results, 2000/01

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 7 Detailed decomposition results, 2004/05

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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	3.33	(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	8.39	3.62	(3.87)	4.19	(3.17)	7.15	(3.95)	7.66	(10.34)
Reweighting error	2.67	2.56	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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 8 Detailed decomposition results, 2008/09

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 9 Detailed decomposition results, 2012/13

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 10 Detailed decomposition results, 2016/17

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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 (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 11 Detailed decomposition results, 2018/19

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
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***	(0.92)
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)	−0.94	1.85	−1.62	(3.10)

Source: LIAB QM2 9317 and Federal Bureau of Statistics (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 and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 12 Aggregate decomposition results for metropolitan areas, actual and robustness check

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
2016/17										
Log wage gap	26.81	0.81	28.78	0.87	28.13	0.75	26.05	0.66	28.83	0.94
Composition effect	22.46	2.10	23.97	1.57	22.96	1.34	19.82	1.78	23.15	2.88
Wage structure effect	4.35	5.94	4.81	4.25	5.17	3.56	6.23	4.85	5.67	8.10
Robustness check										
Log wage gap	26.74	0.89	28.73	0.86	28.07	0.73	26.16	0.65	28.93	0.94
Composition effect	22.44	2.10	23.95	1.56	22.80	1.33	19.79	1.77	23.40	2.85
Wage structure effect	4.29	5.96	4.78	4.23	5.27	3.54	6.37	4.83	5.52	8.05
2018/19										
Log wage gap	23.24	0.98	25.66	0.80	25.30	0.84	26.92	0.67	28.78	0.95
Composition effect	19.85	2.56	22.18	1.62	20.96	1.49	20.58	1.84	23.95	3.20
Wage structure effect	3.38	7.33	3.48	4.47	4.34	4.09	6.37	5.01	4.83	9.06
Robustness check										
Log wage gap	22.80	0.95	25.41	0.79	25.38	0.81	27.05	0.66	28.97	0.95
Composition effect	19.82	2.51	21.09	1.60	20.87	1.45	20.53	1.81	24.25	3.23
Wage structure effect	2.98	7.21	3.51	4.39	4.51	4.0	6.52	4.95	4.71	9.13

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.

Notes: The table presents the results of the aggregate RIF-regressions based OB decomposition approach for metropolitan areas. Both, the actual observed estimations and results of a robustness check using the definition of metropolitan areas in 2015 are presented. All coefficients and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 13 Aggregate decomposition results for non-metropolitan areas, actual and robustness check

	10th percentile		25th percentile		50th percentile		75th percentile		90th percentile	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
2016/17										
Log wage gap	26.92	1.11	29.03	0.76	27.05	0.88	22.66	1.08	17.06	3.08
Composition effect	21.96	1.91	24.26	2.52	21.11	1.81	16.72	2.28	13.06	3.08
Wage structure effect	4.96	6.27	4.77	7.93	5.94	5.52	5.94	7.15	3.99	10.10
Robustness check										
Log wage gap	28.88	1.16	29.14	0.77	26.97	0.89	22.13	1.11	16.28	1.24
Composition effect	20.41	2.89	24.35	2.52	21.33	1.93	16.60	2.32	12.45	2.98
Wage structure effect	6.48	9.50	4.79	7.96	5.64	5.91	5.53	7.33	3.83	9.84
2018/19										
Log wage gap	26.53	0.89	29.97	0.89	28.01	0.70	28.23	0.85	27.80	1.21
Composition effect	20.21	4.98	25.66	2.22	22.01	2.09	18.56	1.91	19.82	3.40
Wage structure effect	6.32	13.27	4.31	6.33	5.99	6.02	9.66	5.42	7.98	10.36
Robustness check										
Log wage gap	27.46	0.91	30.45	0.89	28.06	0.73	27.90	0.88	26.67	1.28
Composition effect	20.28	4.92	25.41	2.36	20.80	2.33	17.88	2.02	19.03	3.41
Wage structure effect	7.17	13.32	5.03	6.82	7.25	8.84	10.02	5.87	7.64	10.41

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.

Notes: The table presents the results of the aggregate RIF-regressions based OB decomposition approach for non-metropolitan areas. Both, the actual observed estimations and results of a robustness check using the definition of metropolitan areas in 2015 are presented. All coefficients and wage gaps above are multiplied by 100 for convenience and represent log percentage points. ***, **, and * indicate statistical significance at the 1, 5, and 10 percent level, respectively. Sampling weights are employed.

Table 14 Robustness check using lagged presence of foreign population, 2000/01–2008/09

	2000/01		2004/05		2008/09	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
10th Percentile						
Total difference	24.75	1.70	22.37	1.14	24.98	1.16
Pure explained	11.70	1.31	13.41	0.76	13.55	0.72
Specification error	3.07	2.53	0.33	2.27	4.88	1.69
Foreign share	-1.72	0.39	1.72	0.13	−5.18	0.52
25th Percentile						
Total difference	16.01	0.65	16.20	0.61	18.45	0.69
Pure explained	10.59	0.58	10.65	0.41	13.21	1.14
Specification error	1.01	1.09	0.45	1.17	5.24	3.69
Foreign share	-1.95	0.23	1.69	0.12	−0.03	0.22
50th Percentile						
Total difference	14.65	0.35	14.11	0.39	16.36	0.46
Pure explained	8.53	0.35	8.58	0.32	11.39	0.40
Specification error	2.33	1.19	1.20	0.98	0.08	0.75
Foreign share	-0.56	0.11	2.35	0.18	2.30	0.20
75th Percentile						
Total difference	22.28	0.37	21.43	0.41	22.33	0.46
Pure explained	12.91	0.59	12.58	0.53	13.45	1.65
Specification error	6.92	1.75	2.88	1.38	1.65	1.25
Foreign share	-0.42	0.16	-0.34	0.13	−0.12	0.07
90th Percentile						
Total difference	30.22	0.54	28.67	0.63	26.54	0.80
Pure explained	24.61	1.12	22.91	3.37	24.00	0.90
Specification error	3.43	2.61	0.58	3.17	−3.34	2.17
Foreign share	-0.70	0.31	2.15	0.26	1.60	0.18

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.
Notes: The table presents the results of the decomposition analyses using lagged data on the presence of foreign population. The shares are multiplied by 100 for convenience. Sampling weights are employed. The results The shares are multiplied by 100 for convenience. Sampling weights are employed.

Table 15 Robustness check using lagged presence of foreign population, 2012/13–2018/19

	2012/13		2016/17		2018/19	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
10th Percentile						
Total difference	27.64	0.91	26.62	0.71	24.08	0.70
Pure explained	14.44	0.54	11.98	0.33	13.14	0.30
Specification error	7.84	1.87	9.25	1.99	4.83	3.24
Foreign share	1.86	0.12	1.94	0.14	0.64	0.14
25th Percentile						
Total difference	23.30	0.71	29.14	0.62	26.90	0.61
Pure explained	18.76	0.54	19.30	0.37	17.38	0.35
Specification error	0.98	1.20	4.32	1.37	5.21	1.27
Foreign share	1.37	0.17	2.15	0.21	1.01	0.15
50th Percentile						
Total difference	19.08	0.49	27.25	0.57	26.45	0.57
Pure explained	14.26	0.51	22.48	0.44	22.77	0.48
Specification error	-0.78	0.91	−0.41	1.03	−1.54	1.09
Foreign share	-1.20	0.20	−0.95	0.10	−1.80	0.21
75th Percentile						
Total difference	22.34	0.51	24.78	0.57	26.56	0.53
Pure explained	14.02	0.63	20.68	0.50	21.08	0.52
Specification error	2.59	1.36	−2.31	1.30	−2.28	1.32
Foreign share	-0.25	0.15	−0.62	0.06	−0.73	0.09
90th Percentile						
Total difference	24.94	0.78	25.29	0.75	27.77	0.76
Pure explained	21.84	1.15	24.11	0.76	26.43	0.92
Specification error	-1.69	2.71	−5.37	2.14	−5.57	2.41
Foreign share	0.62	0.32	−0.42	0.06	−0.19	0.05

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.
Notes: The table presents the results of the decomposition analyses using lagged data on the presence of foreign population. The shares are multiplied by 100 for convenience. Sampling weights are employed.

Table 16 Fixed effects estimation, 2000–2009

	Overall		Metropolitan		Non-Metropolitan	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
10th Percentile						
Total difference	23.92	0.66	25.60	0.79	20.49	1.11
Pure explained	14.72	0.45	14.37	0.49	13.41	0.75
Specification error	1.22	1.12	2.86	1.31	−0.14	1.75
Foreign share	−4.95	0.32	-4.82	0.34	0.05	0.02
25th Percentile						
Total difference	16.43	0.29	17. 96	0.35	14.54	0.50
Pure explained	10.59	0.24	10.92	0.27	10.53	0.43
Specification error	0.69	0.53	0.96	0.61	0.81	0.74
Foreign share	0.94	0.11	0.71	0.11	2.59	0.12
50th Percentile						
Total difference	14.69	0.18	17.18	0.23	11.62	0.29
Pure explained	8.82	0.15	9.89	0.20	7.80	0.26
Specification error	1.13	0.49	1.50	0.46	0.91	0.79
Foreign share	0.61	0.06	0.78	0.07	−0.64	0.08
75th Percentile						
Total difference	22.09	0.19	25.16	0.23	17.47	0.28
Pure explained	12.53	0.02	14.48	0.25	9.91	0.34
Specification error	3.25	0.80	2.00	0.07	4.51	1.81
Foreign share	1.26	0.07	1.70	0.08	−2.06	0.10
90th Percentile						
Total difference	29.41	0.27	32.56	0.34	22.38	0.44
Pure explained	22.03	0.43	26.56	0.55	17.68	0.81
Specification error	1.80	1.23	-0.72	1.42	−0.39	2.32
Foreign share	2.00	0.10	2.10	0.11	−2.70	0.17

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.
Notes: The table presents fixed effects estimation of the decomposition analyses restricted to the effect due to foreign population for the period between 2000 and 2009. The shares are multiplied by 100 for convenience. Sampling weights are employed.

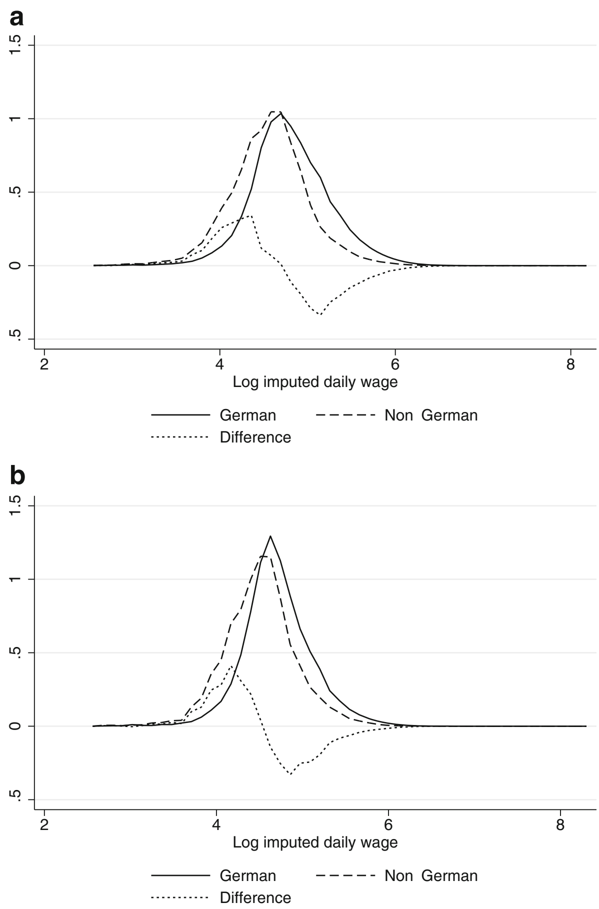
Table 17 Fixed effects estimation, 2012–2019

	Overall		Metropolitan		Non-Metropolitan	
	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.	Coefficient	Robust Std. Err.
10th Percentile						
Total difference	25.84	0.39	25.74	0.51	26.47	0.59
Pure explained	12.19	0.23	11.58	0.03	13.72	0.25
Specification error	8.10	1.15	7.79	1.37	8.97	1.61
Foreign share	2.48	0.29	2.03	0.36	−0.22	0.31
25th Percentile						
Total difference	26.50	0.33	26.21	0.43	27.26	0.48
Pure explained	18.82	0.23	17.73	0.31	20.28	0.28
Specification error	2.98	0.74	3.81	0.80	3.51	1.11
Foreign share	0.90	0.23	0.81	0.27	−2.45	0.27
50th Percentile						
Total difference	23.90	0.28	24.73	0.37	23.77	0.41
Pure explained	19.94	0.25	20.04	0.36	20.14	0.33
Specification error	-1.90	0.59	−1.93	0.63	−2.05	0.92
Foreign share	1.44	0.18	2.04	0.24	−0.97	0.20
75th Percentile						
Total difference	24.19	0.27	26.32	0.33	22.04	0.47
Pure explained	17.84	0.26	18.04	0.31	18.40	0.43
Specification error	-0.87	0.72	−0.19	0.82	−2.83	1.04
Foreign share	0.25	0.16	1.14	0.19	−2.30	0.24
90th Percentile						
Total difference	25.51	0.39	28.77	0.47	19.18	0.73
Pure explained	23.08	0.40	24.25	0.46	21.12	0.74
Specification error	-3.76	1.24	−3.11	1.53	−5.56	1.91
Foreign share	-1.01	0.25	0.35	0.29	−10.99	0.53

Source: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations.
Notes: The table presents fixed effects estimation of the decomposition analyses restricted to the effect due to foreign population for the period between 2012 and 2019. The shares are multiplied by 100 for convenience. Sampling weights are employed.

8.2 Appendix B

Fig. 9 Wage densities, by region **a** Metropolitan regions, **b** Non-Metropolitan regions (*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.)



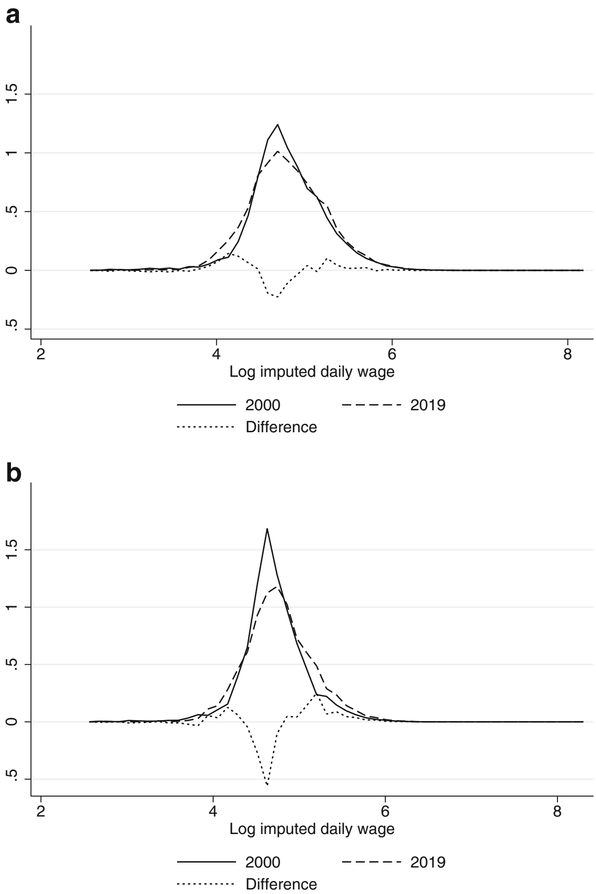
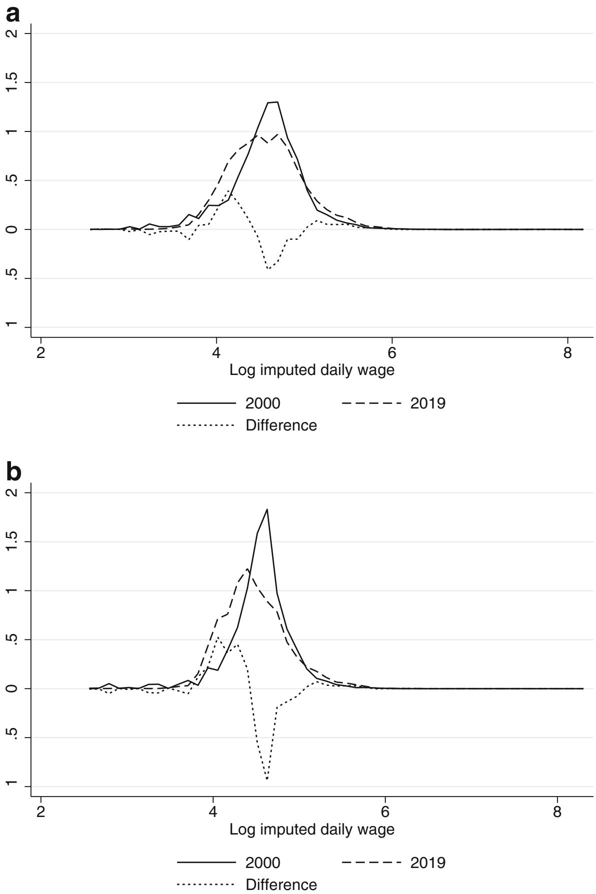


Fig. 10 Wage densities over time, German workers **a** Metropolitan regions, **b** Non-Metropolitan regions (*Source*: LIAB QM2 9319, own calculations. *Note*: The figure presents the kernel density estimations of the wage densities for German workers in Metropolitan and Non-Metropolitan regions for 2000 and 2019. Sampling weights are employed.)

Fig. 11 Wage densities over time, Non-German workers **a** Metropolitan regions, **b** Non-Metropolitan regions (*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.)



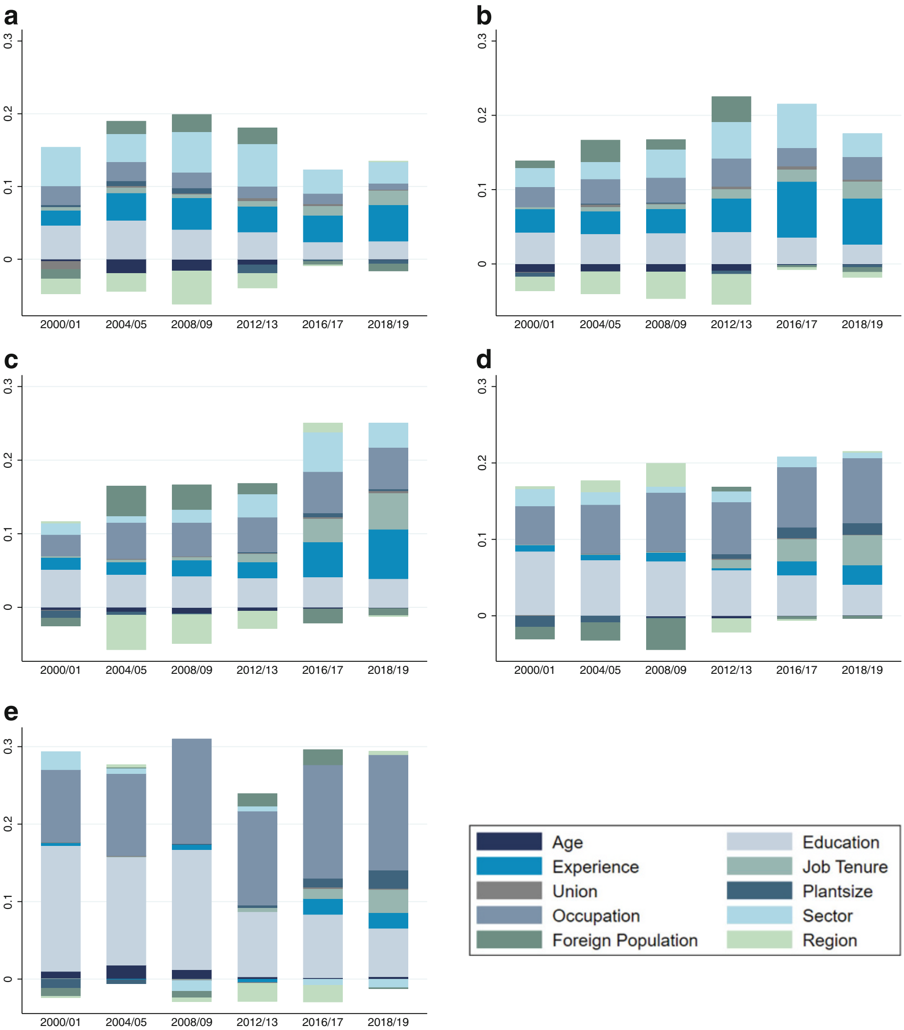


Fig. 12 Detailed decomposition of the explained part in metropolitan areas, 2000–2019 **a** 10th percentile, **b** 25th percentile, **c** 50th percentile, **d** 75th percentile, **e** 90th percentile (*Source*: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations. *Notes*: The different subfigures present the estimated results of the RIF-regressions based detailed OB decompositions in metropolitan areas. Sampling weights are employed.)

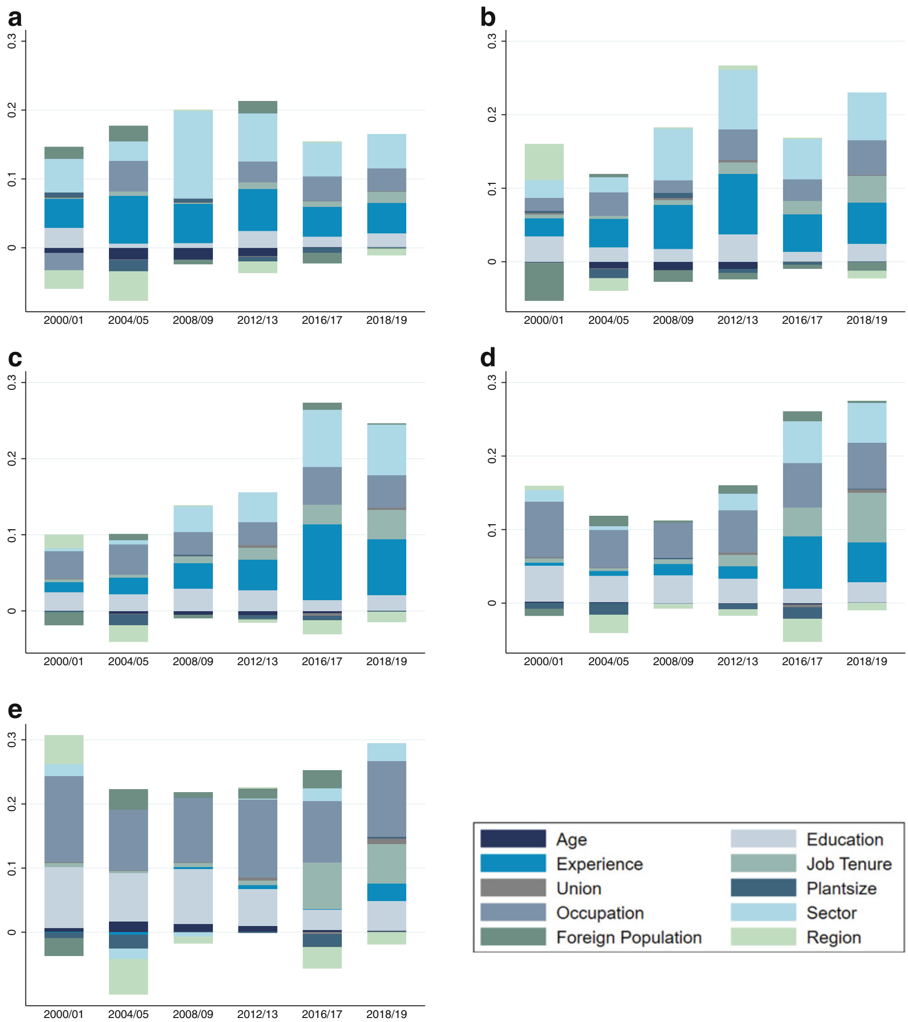


Fig. 13 Detailed decomposition of the explained part in non-metropolitan areas, 2000–2019 **a** 10th percentile, **b** 25th percentile, **c** 50th percentile, **d** 75th percentile, **e** 90th percentile (*Source*: LIAB QM2 9319 and Federal Bureau of Statistics (2021a), own calculations. *Notes*: The different subfigures present the estimated results of the RIF-regressions based detailed OB decompositions in non-metropolitan areas. Sampling weights are employed.)

8.3 Appendix C

8.3.1 Robustness checks

Metropolitan areas. 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 (2022) in 2008 (Kawka 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 (2022) in 2015. The estimated results show no differences regarding the size and decomposition of the wage gaps (see Tables 12 and 13 in Appendix A).

Presence of foreign population. 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 (see Tables 14 and 15 in Appendix A). The estimated results reveal no differences regarding the effect on explained and unexplained parts of detailed wage gap decompositions.

Pooled fixed effects estimations. In order to provide estimates of a model for all years jointly, fixed effects estimations are additionally conducted for the decomposition analyses. Therefore, two pooled time periods are defined, 2000–2009 and 2012–2019.[35] The results presented in Tables 16 and 17 in Appendix A present mainly highly significant positive effects due to the presence of foreign population in the overall sample supporting the estimations presented in the main text. For the metropolitan area the results are as well positive and significant indicating once more a possible relationship between a higher presence of foreign population and higher wage gaps between German and Non-German workers. On the opposite, the results for the non-metropolitan areas are mainly negative or not statistically significant. Overall, the findings again support the results of on average higher wage gaps between native and immigrant workers in metropolitan areas compared to non-metropolitan areas. In this context, an additional fixed-effects estimation is conducted as an additional robustness check on the higher wage gaps in urban areas. Using the pooled sample of both areas, the effects of a dummy variable indicating metropolitan areas is statistically significant as well as positive and thus supporting once again the above mentioned results.

[35] Due to a change in the reporting procedure of the social security agency, a considerable increase in the number of missing values occurs in the years around 2010 in the underlying data. As a result of this, the fixed effects estimation is divided into two subperiods.

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References

Aldashev A, Gernandt J, Thomsen SL (2012) The immigrant-native wage gap in Germany. Jahrb Natl Okon Stat 232(5):490–517
Barsky R, Bound J, Charles KK, Lupton JP (2002) Accounting for the black-white wealth gap. J Am Stat Assoc 97(459):663–673
Bartolucci C (2014) Understanding the native–immigrant wage gap using matched employer-employee data: evidence from Germany. ILR Rev 67(4):1166–1202
Baumgarten D, Felbermayr G, Lehwald S (2020) Dissecting between-plant and within-plant wage dispersion: evidence from Germany. Ind Relat 59(1):85–122
BBSR Bonn (2019) Laufende Raumbeobachtung des BBSR
Beaman LA (2011) Social networks and the dynamics of labour market outcomes: evidence from refugees resettled in the U.S. Review of Economic Studies 79(1):128–161
Bertrand M, Luttmer EFP, Mullainathan S (2000) Network effects and welfare cultures. Q J Econ 115(3):1019–1055
Beyer RCM (2019) Wage performance of immigrants in Germany. Ger Econ Rev 20(4):e141–e169
Biewen M, Juhasz A (2012) Understanding rising income inequality in Germany, 1999/2000–2005/2006. Rev Income Wealth 58(4):622–647
Biewen M, Seckler M (2019) Unions, internationalization, tasks, firms, and worker characteristics: a detailed decomposition analysis of rising wage inequality in Germany. J Econ Inequal 17:461–498
Biewen M, Ungerer M, Löffler M (2019) Why did income inequality in Germany not increase further after 2005? Ger Econ Rev 20(4):471–504
Blinder AS (1973) Wage discrimination: reduced form and structural estimates. J Hum Resour 8(4):436–455
Borjas GJ (2000) Ethnic enclaves and assimilation. Swed Econ Policy Rev 7(2):89–122
Borjas GJ (2014) Immigration economics. Harvard University Press, Cambridge
Brixy U, Brunow S, Ochsen C (2022) On the peripheral-urban wage gap in Germany. Appl Geogr 139:102647
Brunow S, Jost O (2019) Wages of migrant and native employees in Germany: New light on an old issue. IAB-discussion paper, vol 10/2019
Brunow S, Jost O (2021) Foreign vs. German wage differentials in Germany: does the home country matter? In: Labor markets, migration, and mobility. Springer, Singapore, pp 55–76
Brunow S, Jost O (2022) Wages of skilled migrant and native employees in Germany: new light on an old issue. Int Migr Rev 56(2):410–432
Buch T, Hamann S, Niebuhr A, Rossen A (2014) What makes cities attractive? The determinants of urban labour migration in Germany. Urban Stud 51(9):1960–1978
Card D (2009) Immigration and inequality. Am Econ Rev 99(2):1–21
Diller C, Eichhorn S (2022) 25 Jahre Metropolregionen in Deutschland im Spagat zwischen Raumordnung und Raumentwicklung. Ein Klassifizierungsvorschlag. Standort 46:16–23. https://doi.org/10.1007/s00548-021-00760-4
DiNardo J, Fortin NM, Lemieux T (1996) Labor market institutions and the distribution of wages, 1973–1992: a semiparametric approach. Econometrica 64(5):1001–1044
Dorn D, Zweimueller J (2021) Migration and labor market integration in Europe. J Econ Perspect 35(2):49–76

Dustmann C, Ludsteck J, Schönberg U (2009) Revisiting the German wage structure. Q J Econ 124(2):843–881
Facchini G, Lodigiani E (2014) Attracting skilled immigrants: An overview of recent policy developments in advanced countries. Natl Inst Econ Rev 229:R3–R21
Federal Bureau of Statistics (Destatis) (2021a) Genesis-Online
Federal Bureau of Statistics (Destatis) (2021b) Bevölkerung und Erwerbstätigkeit – Ausländische Bevölkerung/Ergebnisse des Ausländerzentralregisters
Felbermayr G, Baumgarten D, Lehwald S (2014) Increasing wage inequality in Germany: what role does global trade play? In: Docbase – Publication Database of the CESifo Group
Firpo S, Fortin NM, Lemieux T (2009) Unconditional quantile regressions. Econometrica 77(3):953–973
Firpo SP, Fortin NM, Lemieux T (2018) Decomposing wage distributions using recentered influence function regressions. Econometrics 6(2):1–40
Fortin N, Lemieux T, Firpo S (2011) Chapter 1 – decomposition methods in economics. In: Ashenfelter O, Card D (eds) Handbook of labor economics, vol 4. Elsevier, Amsterdam, pp 1–102
Fuchs J, Weber B (2018) Fachkräftemangel: Inländische Personalreserven als Alternative zur Zuwanderung. Technical report. IAB-discussion paper
Gartner H (2005) The imputation of wages above the contribution limit with the German IAB employment sample. FDZ Methodenreport, vol 02/2005. Institut für Arbeitsmarkt- und Berufsforschung (IAB), Nürnberg
Glitz A (2014) Ethnic segregation in Germany. Labour Econ 29:28–40
Gould ED (2007) Cities, workers, and wages: A structural analysis of the urban wage premium. Rev Econ Stud 74(2):477–506
Heuermann D, Halfdanarson B, Suedekum J (2010) Human capital externalities and the urban wage premium: Two literatures and their interrelations. Urban Stud 47(4):749–767
Ingwersen K, Thomsen SL (2021) The immigrant-native wage gap in Germany revisited. J Econ Inequal. https://doi.org/10.1007/s10888-021-09493-8
Initiative circle European metropolitan regions in Germany (IKM) (2022) https://deutsche-metropolregionen.org. Accessed 2 Feb 2022
Jann B (2008) The blinder–oaxaca decomposition for linear regression models. Stata J 8(4):453–479
Kaltwasser L, Schludi M (2022) Deutschland im demografischen Dilemma: Woher sollen die Arbeitskräfte kommen? In: IAB-Forum 9. August 2022
Kanas A, Chiswick BR, van der Lippe T, van Tubergen F (2012) Social contacts and the economic performance of immigrants: a panel study of immigrants in Germany. Int Migr Rev 46(3):680–709
Kawka R (2016) Metropolregionen–Kooperation und Wettbewerb in Deutschland und Europa. Informationen zur Raumentwicklung 2016(5)
Kühn M (2018) Immigration strategies of cities: local growth policies and urban planning in Germany. Eur Plan Stud 26(9):1747–1762
Lehmer F, Ludsteck J (2011) The immigrant wage gap in Germany: Are east europeans worse off? Int Migr Rev 45(4):872–906
Michel D (1998) Das Netz der europäischen Metropolregionen in Deutschland. Raumforsch Raumordn 56(5):362–368
Oaxaca R (1973) Male-female wage differentials in Urban labor markets. Int Econ Rev 14(3):693–709
OECD (2018) Germany policy brief – Migration: using migraton to meet skill shortages. Technical report
OECD (2019) International migration outlook 2019
Ohlert C, Beblo M, Wolf E (2016) Competition, collective bargaining, and immigrant wage gaps within German establishments. In: Wage inequality in Germany and the role of organisations, vol 87
Ottaviano GIP, Peri G (2012) Rethinking the effect of immigration on wages. J Eur Econ Assoc 10(1):152–197
Ottaviano GIP, Peri G (2012) The effects of immigration on US wages and rents: A general equilibrium approach. In: Migration impact assessment. Edward Elgar, Cheltenham
Ruf K, Schmidtlein L, Seth S, Stüber H, Umkehrer M (2021) Linked-Employer-Employee-Daten des IAB: LIAB-Querschnittmodell 2 (LIAB QM2) 1993–2019. Technical report, Institut für Arbeitsmarkt-und Berufsforschung (IAB), Nürnberg
Rusche KM, Oberst CA (2010) Europäische Metropolregionen in Deutschland–eine regionalökonomische Evaluation. Raumforsch Raumordn 68(4):243–254
Sauer S, Wollmershäuser T (2021) Fachkräftemangel wird zunehmend zur Belastung für die deutsche Wirtschaft. Ifo Schnelld Digit 2(17):1–4
Schaffner S, Treude B (2014) The effect of ethnic clustering on migrant integration in Germany. SSRN J. https://doi.org/10.2139/ssrn.2579732

Seibert H, Wapler R (2020) Immigration to Germany: Many high-skilled, but also many unskilled. IAB-Kurzbericht, vol 08/2020, p 12

Warman C (2007) Ethnic enclaves and immigrant earnings growth. Can J Econ 40(2):401–422

Winke T (2018) Being close to ethnic peers: the formation of ethnic residential clustering from a household perspective. J Ethn Migr Stud 44(11):1932–1953

Yankow JJ (2006) Why do cities pay more? An empirical examination of some competing theories of the urban wage premium. J Urban Econ 60(2):139–161